A COST BENEFIT ANALYSIS OF OPERATIONAL RISK QUANTIFICATION METHODS FOR REGULATORY CAPITAL

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ABSTRACT

Operational risk has attracted a sizeable amount of attention in recent years as a result of massive operational losses that headlined financial markets across the world. The operational risk losses have been on the back of litigation cases and regulatory fines, some of which originated from the 2008 global financial crisis. As a result it is compulsory for financial institutions to reserve capital for the operational risk exposures inherent in their business activities. Local financial institutions are free to use any of the following operational risk capital estimation methods: Advanced Measurement Approach (AMA), the Standardized (TSA) and/ the Basic Indicator Approach (BIA). The BIA and TSA are predetermined by the Reserve Bank, whilst AMA relies on internally generated methodologies. Estimation approaches employed in this study were initially introduced by the BCBS, largely premised on an increasingly sophisticated technique to incentivise banks to continually advance their management and measurement methods while benefiting from a lower capital charge through gradating from the least to the most sophisticated measurement tool. However, in contrast to BCBS's premise, Sundmacher (2007), whilst using a hypothetical example, finds that depending on a financial institution's distribution of its Gross Income, the incentive to move from BIA to TSA is nonexistent or marginal at best. In this thesis I extend Sundmacher (2007)'s work, and I test one instance of AMA regulatory capital (RegCap) against that of TSA in a bid to crystalise the rand benefit that financial institutions stand to attain (if at all) should they move from TSA to AMA. A Loss Distribution Approach (LDA), coupled with a Monte Carlo simulation, were used in modelling AMA. In modelling the loss severities, the Lognormal, Weibull, Burr, Generalized Pareto, Pareto and Gamma distributions were considered, whilst the Poisson distribution was used for modelling operational loss frequency. The Kolmogorov-Smirnov and Akaike information criterion tests were respectively used for assessing the level of distribution fit and for model selection. The robustness and stability of the model were gauged using stress testing and bootstrap. The TSA modelling design involved using predetermined beta values for different business lines specified by the BCBS. The findings show that the Lognormal and Burr distributions best describes the empirical data. Additionally, there is a substantial incentive in terms of the rand benefit of migrating from TSA to AMA in estimating operational risk capital. The initial benefit could be directed towards changes in information technology systems in order to effect the change from TSA to AMA. Notwithstanding that the data set used in this thesis is restricted to just one of the "big four banks" (owing to proprietary restrictions), the methodology is representable (or generalisable) to the other big banks within South Africa. The scope of this study can further be extended to cover Extreme Value Theory, Non-Parametric Empirical Sampling, Markov Chain Monte Carlo, and Bayesian Approaches in estimating operational risk capital.

DEDICATION

I wish to dedicate this research project to my parents and my three siblings for their unfaltering and visionary support upon which I concede that my academic endeavors are a product that owes much to their contributions.

ACKNOWLEDGEMENTS

I am indebted to Associate Professors: Kanshukan Rajaratnam and Francois Toerien, my supervisors and mentors, for the unparalleled guidance and patience in the supervision of this study. Their advice, support and constructive criticism was and will always be greatly appreciated without which the successful completion of this research would not have been possible. For that, I do promise to pay it forward and also pass knowledge I have gathered to all those in need of it and apply it where it is needed.

DECLARATION

I, Mandla Nyathi, certify that this thesis is my own work, that all material which is not my own has been properly cited and referenced and that this thesis is not concurrently being submitted for any degree other than that of Master of Commerce in Financial Management at the University of Cape Town.

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LIST OF ACRONYMS AND ABBREVIATIONS

AD	Anderson Darling
AEP	Annual Exceedance Probability
ADup	Modified Quadratic Anderson Darling
AggL	Aggregate Loss
AIC	Akaike Information Criterion
AMA	Advanced Measurement Approach
ASA	Alternative Standardised Approach
BCBS	Basel Committee on Banking Supervision
BDSF	Business Disruption and System Failure
BEICFs	Business Environment and Internal Control Factors
BIA	Basic Indicator Approach
CFPB	Consumer Financial Protection Bureau
CPBP	Clients, Products and Business Practices
CvM	Cramer-von Mises
DPA	Damage to Physical Assets
EDPM	Execution, Delivery and Process Management
EF	External Fraud
EL	Expected Loss
ELD	External Loss Data
EPWS	Employment Practices and Workplace Safety
EVT	Extreme Value Theory
GI	Gross Income
GOF	Goodness of Fit
IF	Internal Fraud
ILD	Internal Loss Data
KRI	Key Risk Indicator
KS	Kolmogorov Smirnov
LDA	Loss Distribution Approach
LDCE	Loss Data Collection Exercises
MCMC	Markov Chain Monte Carlo
ML	Money Laundering
MLE	Maximum Likelihood Estimation
ORC	Operational Risk Class
ORX	Operational Riskdata eXchange Association
QIS-4	Quantitative Impact Study 4
RCSA	Risk and Control Self-Assessment
RMG	Risk Management Group
SARB	South African Central Bank
TSA	The Standardised Approach
UL	Unexpected Loss
USD	United States Dollar
VaR	Value at Risk

CHAPTER 1
INTRODUCTION

1.1 Introduction

This decade has been a watershed period for operational risk, largely characterized by massive operational losses that headlined financial markets across the world. The operational risk losses are on the back of litigation cases and regulatory fines, some of which are said to have originated from the 2008 global financial crisis. Litigation on average follows a life cycle that takes between 5 and 8 years to move from inception to settlement or a court decision[1]. These lawsuits and the resultant settlement amounts between the parties have been publicly divulged by the courts due to public interest in the cases, and the huge amounts involved. Additionally, as these losses are finalised, they will form part of the banks' operational loss databases, creating a challenge for banks using loss data dependent modelling[1]. Thus, the ultimate inclusion of these sizeable settlements has caused a considerable upward spike in the regulatory capital charge for banks across the board[1]. To demonstrate the sheer size of some of these operational risk related loss events, the ORX Association News's top five largest loss events for June 2015 are: the API Premiere loss, where around 29,000 investors are believed to have lost a total of USD 1.2 billion after being misled by API Premiere Swiss Trust as part of a fraudulent investment scheme; the Julius Baer provisions of USD 350 million to settle a US Department of Justice investigation regarding its alleged role in enabling US citizens to evade taxes; and PHH Corporation's USD 109 million penalty to be paid to the Consumer Financial Protection Bureau (CFPB) after it was found to have engaged in a mortgage insurance kickback scheme, to name but a few.[2] On the local South Africa front, administrative penalties totaling R125 million in 2014 were levied against Nedbank, ABSA, Standard Bank and FNB for contravening a provision of the Financial Intelligence Centre Act, No 38 of 2001. The central bank additionally issued directives to the four institutions to take remedial action to address specific areas of deficiencies.[3]

Because operational risk losses are unpredictable most of the time, and can be substantial as shown above, the management of operational risk is fast becoming a primary concern for executive management of financial institutions[1]. This greater focus and attention on operational risk management has additionally been strongly advocated by the BCBS and regulators world-wide (inclusive of our local South African Reserve Bank [SARB]), compelling banks to employ risk sensitive approaches (which are deemed to be advanced compared to quantification methodologies that use multiples of gross income [GI]). The Basel II Capital Accord (issued by BCBS in 2006, and its subsequent guidance

[1] http://www.risk.net/journal-of-operational-risk/journal/2385883/latest-issue-of-the-journal-of-operational-risk-94
[2] http://www.orx.org/Pages/LatestNews.aspx
[3] https://www.resbank.co.za/publications/detail-item-view/pages/publications.aspx?sarbweb=3b6aa07d-92ab-441f-b7bf-bb7dfb1bedb4&sarblist=21b5222e-7125-4e55-bb65-56fd3333371e&sarbitem=6196

notes), and the South African Central Bank (SARB), give local banks the option of choosing four alternatives which they may opt to use to quantify operational risk capital. Regulatory capital is the perceived amount that is required by a regulator (typically concerned with systemic risks) for the bank to continue operating and be solvent. The four approaches are the Basic Indicator Approach (BIA), the Standardised Approach (TSA), the Alternative Standardised Approach (ASA), and the Advanced Measurement Approach (AMA). The BIA has no prerequisites with regard to governance frameworks and/ measurement tools. The regulatory capital requirement is mathematically a product of the global GI and a constant factor (BCBS, 2006). Financial institutions are required to map or chart a series of regulatory (Basel II) business lines (BL) to their internal business lines when using TSA and ASA. Basel predetermined beta factors are then multiplied by the GI of each business line to attain the regulatory capital charge for that respective business line. The business line and their respective beta factors are Corporate Finance (18%), Trading and Sales (18%), Retail Banking (12%), Commercial Banking (15%), Payment and Settlement (18%), Agency Services (15%), Asset Management (12%), and Retail Brokerage (12%) (BCBS, 2006). The sum of the underlying business line's capital requirements becomes the requisite regulatory capital for the bank. TSA and ASA elaborate on the BIA by increasing the level of granularity on the bank's activities into the eight underlying business lines mentioned above (BCBS, 2006). For TSA and ASA, there is need for robust risk management, innovative measurement tools and a refined governance framework that needs to be in place prior to being granted the liberty to use them to quantify operational risk capital, albeit all of which come at a substantial cost (BCBS, 2006). Lastly, for AMA financial institutions use internal risk variables and their own empirical model to quantify their operational risk capital reserves that are reported to the Central Bank, and the corresponding economic capital which is a base number for a bank's pricing engine (BCBS, 2006).

Sundmacher (2007) identifies BCBS's premise of thought for introducing the varied operational risk quantification options that have an increasing degree of sophistication, as a means to incentivise financial institutions to apply improved management and measurement methods in exchange for a capital reduction as they move from the least to the most sophisticated measurement tool. However, compliance costs will arise as financial institutions are mandated to meet specified yardsticks when using TSA or AMA. This thesis centers on the realization that financial institutions have to make this monetary investment in order to move from TSA to AMA. However, the benefit for moving to AMA is not readily obvious. In this thesis I extend Sundmacher (2007)'s work, and test one instance of AMA regulatory capital against that of TSA in a bid to crystalise the rand benefit (if any) that South African financial institutions stand to attain should they move from TSA to AMA. Using this illustrated process South African domiciled banks can calculate the rand benefit for multiple years. Given multiple year benefit one may determine the threshold of initial investment for the bank. This initial cost would be for changes in IT systems in order to effect the change from TSA to AMA. It must be noted however that the goal of the thesis is *not* to explicitly measure the costs of the switch but to determine whether the benefits are such that they would warrant a bank then assessing the costs of switching. In adopting AMA, a significant number of international financial institutions are on a Loss Distribution Approach (LDA). In conducting this cost benefit analysis, emphasis is placed on all key building blocks of a typical LDA.

1.2 Background to the study

Operational risk is fast becoming one of the leading risks South African banks are faced with in today's integrated and complex global economy. An overview of the past two decades reveals that operational failure has often been a major component leading to insolvency of many otherwise successful and profitable banks, owing to the unpredictability of operational losses[4]. Examples of some large international institutions that suffered substantial operational risk losses are Drexel, TWA, Barings, Maxwell, Olympia and York, Enron and Global Crossing[5]. Additionally, where large market or credit losses have taken place, operational failure is often largely part and parcel, if not the root cause. On the South African front, a classical example is the recent demise of ABL owing to an inadequate provisioning policy, despite considerable asset write-downs by African Bank's management[6]. Thus at board level, the accurate quantification of operational risk has become a focal point for the bank's senior executives to understand where their largest exposures are. By analysing risk levels of the bank's full loss profile of the existing business and control environment, executives are able to make informed risk transfer, capitalisation and/ mitigation decisions. This mentioned process also creates a greater platform to demonstrate that the banks' operational risk strategies are consciously aligned with the risk appetite and tolerance standards of banks' boards and other stakeholders. Looking at the balance sheets of some of South Africa's financial institutions, operational risk is seemingly starting to be given due recognition as a pivotal risk component, as indicated by the mitigation and transfer costs linked to this risk.

1.2.1 Regulatory requirements for AMA

In order to secure approval from the SARB to use AMA, model compliance with the requirements of the local regulator, the International Standards and Guidelines for modelling operational risk, and those of the internal business's governance structures, has to be achieved. BCBS (2006) highlights the following key qualitative and quantitative criteria for a bank to attain or maintain its AMA status:

a) A bank must capture potential severe loss events in its Operational Risk Modelling approach;

[4] See also http://www.bdlive.co.za/world/americas/2015/08/24/banks-lose-260bn-to-fines-and-lawsuits
[5] https://www.bis.org/publ/gten06b.pdf and (Fatima Z.E.A & Said H, 2014)
[6] http://www.biznews.com/thought-leaders/2015/05/06/african-bank-how-we-managed-the-collapse/

b) A bank's Operational Risk Approach must be sound – comparable to a one year holding period, and at 99.9th percent confidence interval;
c) A bank must have and maintain strenuous operational risk model development and independent model validation procedures;
d) Regulatory capital must be: expected loss (EL) + unexpected loss (UL), unless permission has been granted by the relevant regulators to implement additional capital discounts;
e) A bank's measurement system must capture severe infrequent possible loss events that drive the operational risk capital requirements. This may be achieved by an appropriate granularity selection.
f) No diversification is permitted, unless specific express sanction is given by the SARB.
g) A sound operational risk system must include scenario analysis, internal loss data (ILD), relevant external data, and factors reflecting the business environment and internal control systems, and must be well documented to aid validation and third party audit.

1.3 Statement of the problem and rationale

The Basel II definition of operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events (BCBS, 2006). Thus by extension operational risk cannot be fully eliminated as long as there are people, systems and processes that are imperfect by design or omission. Operational risk events are due to a myriad of factors some of which are fraud, technology failures, improper business practices, natural disasters and product flaws to name but a few (De Jongh, De Jongh, De Jongh and van Vuuren, 2012). Operational risk is distinct from market and credit risk, however there are instances were large market or credit losses have taken place owing to operational failure being largely part and parcel, if not their root cause. Some of the complexities relating to the management and quantification of operational risk is the difficulties in reverse engineering the components that make up the VaR. However, for credit and market risk it is possible to determine each risk factor that makes up the ultimate VaR (Laycock, 2014).

Financial institutions are not presently able to hedge their exposure to operational risk through asset securitization, despite operational risk fast becoming a larger share of their total risk exposure. The sizable operational losses that financial institutions have suffered as noted by Dutta and Perry (2006) has led to increased attention to operational risk. Froot (2003) argues that the increased focus on operational risk is driven by the potential devastating ability of operational losses to trigger systemic losses across the financial system (and illiquidity). For many South African banks the efficient measurement and management of operational risk is an evident opportunity that can lead to increased net worth of the business, through minimizing the amount of risk relative to the earnings of the bank. Given the basic understanding of shareholder value, an asset is valued by estimating the net present value of its future cashflows, adjusted for risk[7] - thus, by extension, value can also be added by reducing the risk associated with the bank's earnings (BCBS, 2003a). To achieve such value addition, an alternate route could be for South African financial institutions is to incorporate more sophisticated measurement techniques to increase shareholder value. AMA is viewed by BCBS (2006) as contributing to managing for value by introducing operational risk management systems designed to improve value by generating improved operational risk management capability, and delivering capital relief in the process.

However, the requirements for AMA are that financial institutions implement an operational risk management methodology and overarching framework that will serve the purposes of modelling operational risk in a systematic way, which brings with it varied costs for the institution. So, notwithstanding that a bank is required to hold capital to absorb unexpected losses, the bank's capital is also its shareholders' investment, and a certain minimum level of financial return is expected. Accordingly, risk and capital should be well-understood, managed and optimised. By making the transition from TSA to AMA, capital optimisation is thought to be achieved due to the fact that internal data, together with informed, structured scenario analysis using an external database, can be used in the calculation of both economic and regulatory capital charges that take into account the idiosyncrasies of the bank in question. As opposed to the use of generic beta factors dictated by Basel II, that are not risk sensitive nor do they take cognizance of the idiosyncrasies of each bank.

Snyman (2011) noted that South African banks (63 local and foreign controlled banks as per the SARB[8]) are largely making use of the BIA or TSA approaches (or variations of the two), mainly due to the following identified reasons: immaturity of AMA within the South African financial markets, the lack of succinct industry standards and guidance, the need for complicated risk management processes, measurement instruments and frameworks, as well as the prerequisite of robust governance structures needed to fully implement AMA (all of which come with significant cost implications). Additionally, for the handful of banks that are on AMA globally, one of the biggest concerns for operational risk in AMA institutions is, despite having assumed the cost of implementing AMA, they are presently growing worries by regulators, which center on the validity of the capital models that are giving wildly differing results from bank to bank[9]. This observation is premised in the observed range of practices (AMA) (Range of Practice Paper) which describes discrepancies in industry practices resulting in differing results.[10] The end result for South African banks that are considering gradating to AMA is increased rigorous model governance and conforming requirements, thus by extension further increasing the implementation and compliance costs.

[7] http://people.stern.nyu.edu/adamodar/pdfiles/valrisk/ch5.pdf

[8] https://www.resbank.co.za/RegulationAndSupervision/BankSupervision/Pages/SouthAfricanRegisteredBanksAndRepresentativeOffices.aspx

[9] www.bis.org/publ/bcbs160.htm

[10] www.bis.org/publ/bcbs160.htm

BCBS (2011) has been encouraging the gradation to AMA, and also highlighting the shortcomings of BIA, TSA and ASA, chief of which being that none of these approaches are risk sensitive (Sundmacher, 2007). The BCBS sees this as inevitably holding back the financial institutions from driving the appropriate risk management behavior which is afforded by AMA, owing to AMA being risk sensitive (Synman, 2011). When appropriately implemented it (or thought to) effectively rewards managers that reduce their exposure to operational risk by reducing their respective capital requirements, and penalises those that are risk tolerant (or risk lovers) by nudging up their capital requirements. Though the regulators are advocating for AMA, one has to take cognizance of one of the biggest criticism against AMA, being that if a bank was on AMA and a large fine for tax avoidance was incurred (some eight years ago), this loss would have to be included in its operational risk data set, effectively causing a spike in the capital charge. This would be the case even though the bank in question may since have addressed the underlying problem (for example, by overhauling a subsidiary where the loss emanated from or, by getting rid of implicated clients).

From the above background, it is evident that operational risk has become an area of paramount interest in the banking industry. The size of operational risk losses as a result of the intricacies of banking practices, products and market players has made the financial community more aware of the grave need for banks to be able to effectively measure and manage their respective operational risk exposures. This thesis extends Sundmacher's (2007) work, and tests one instance of AMA regulatory capital against that of TSA in a bid to crystalise the rand benefit that South African financial institutions stand to attain (if at all) should they move from TSA to AMA. Using this illustrated process banks can calculate the rand benefit for multiple years. Though, I limit the scope of the work to calculating a one-year benefit, forecasting multiple year benefit will help to determine the threshold of initial investment for a bank. The largest four banks "the big four" in South Africa have a combined market capitalisation of R647Bn[11] (Nedbank R91.96Bn, FirstRand Limited 253.15Bn, Standard Bank Group R181.26Bn and Barclays Africa Group R121.52Bn as at 9 February, 2016). These four banks account for approximately 85% of South African market share.[12] Capitec, another big bank in South Africa, has a differing operational risk profile owing to its use variant operating model. For all the four big banks (i.e., Nedbank, FirstRand Limited, Standard Bank Group and Barclays Africa Group), their ILD is regarded as proprietary information. This effectively limited the amount of data that could be accessed for this thesis. However, I did managed to collate one set of data that belongs to one of the big four banks. Notwithstanding that the data set is restricted to just one of the big four, the scope of this thesis is to illustrate a methodology that is representable (or generalisable) to the other big banks within South Africa (as affirmed by the ORX bench marking results in Chapter 3 of thesis, under section 3.3).

[11] https://www.google.com/finance?q=JSE%3ANED&ei=R4u5VrHRM9fQUd_8l_AF
[12] (http://internationalbanker.com/banking/recent-developments-in-south-african-banking/).

The above is achieved through addressing the following research objectives:

a) To outline an Operational Risk Management Framework and Quantification Method for Regulatory Capital using the AMA.

b) To apply the proposed Operational Risk Management Framework and Quantification Method for Regulatory Capital to empirical data.

c) To apply the Standardised Approach (TSA) to empirical data mentioned in the previous point (b), and compute the capital benefit by calculating the difference between TSA capital against AMA capital.

d) To critically test the rand benefit (on one instance of bank data) of gradating from the TSA to the AMA (TSA–AMA regulatory capital).

1.4 Chapter summary and structure outline

This chapter introduced operational risk at a global level and then considered the South African context. The importance of operational risk modelling was also highlighted and some case examples were provided to show how crucial operational risk management is. It is clear that operational risk has attracted attention in the banking industry at large. TSA which is viewed as being simplistic in nature, with limited sophisticated requirements is an alternate quantification method discussed in the chapter. Its rivalry is AMA, AMA offers potential long run benefits although it comes at a cost, expressed in terms of compliance costs. Therefore, this thesis focuses on providing an operation risk management framework when using the AMA model. Furthermore, it applies the framework to empirical data and assesses the potential benefits of migrating from TSA to AMA. The remainder of this thesis is structured as follows: the next chapter gives a comprehensive literature and technical study discussing prior literature on the quantification of operational risk, the building blocks of operational risk capital modelling practices, techniques and methodologies for both TSA and AMA. In chapter 3 the data and research methodology is discussed and the conceptual framework provided, whilst in chapter 4 the substantial benefits that may be attained when a South African bank moves from TSA to the AMA are illustrated. Chapter 5 concludes the study.

CHAPTER 2
LITERATURE AND TECHNICAL REVIEW

2.1 Introduction

The structure and approach to the literature review is premised on Sundmacher (2007)'s case study based analysis in light of the limited access to other bank's proprietary data. Sundmacher (2007) assesses the case of a financial institution moving from the BIA to the TSA, using hypothesized data and he finds that there might be little incentive for financial institutions to move from BIA to TSA. The only exception to this finding is where GI generation lies in the low-beta business units. This thesis extends the work of Sundmacher (2007) and tests the case of a financial institution moving from TSA to AMA. The following section is a deep dive into prior research on AMA and TSA, focusing on the complexities of quantifying operational risk as well as the overall need / justification for this thesis (to ascertain if there is a definitive answer to the research question, in particular for the South African banks). The author's intention in preparing this work is to be as pragmatic as possible, shying away from more statistical sophistication than necessary.

2.2 Prior research on AMA and TSA

Some of the estimation approaches employed in this thesis were initially introduced by the BCBS, largely premised on an increasingly sophisticated approach to the quantification of capital to incentivise banks to improve their measurement and management of risk while benefiting from a lower capital charge through gradating from the least to the most sophisticated measurement tool. Francesco and Ardita (2012) test the validity of this implicit benefit. They assess the profitability of using AMA through a cost–benefit analysis for Albanian financial institutions. In the process, they identify some of the main hurdles that Albanian banks face in the implementation of AMA. There are two distinct branches of AMA identified that is, the LDA and the Internal Measurement Approach. Francesco and Ardita (2012), highlight the use of External Data (ED) in Scenario Analysis (referred to as an indirect method of using ED). In using the alternate method, referred to as the direct LDA approach, external data is initially treated in any of the following ways: linear adjusting the data to the institution's dimensions; using coefficients for each type of event using regression; applying a data filter (to ensure that the data relates to a similar sized bank) and a fourth alternative that requires no adjustment, but where the data is just integrated into the modelling process. The paper also touches on the various options for integrating the internal and external data. The mentioned techniques are Qualitative Integration (which is used in this thesis), Bayesian Aggregation, and Convolution. Francesco and Ardita (2012) highlight the pervasive challenge within operational risk of lack of information or data either internal data or external data within Albania. The solution that they suggest is the use of Scenario

Analysis, or the incorporation of additional data. The additional data referred to would seem to allude to the use of External Data, through Extreme Value Theory (Body, and Tail modelling), which is suggested as an area of further study in this thesis. The complexities in the quantification of operational risk using AMA are highlighted as data shortage, the nature of operational risk, and the lack of a strong risk sensitive exposure measure in operational risk modelling. For the Albanian market, they also touch on the challenge of obtaining at least five years' worth of historical loss data prior to a bank being allowed the right to quantify its risk using AMA – this being a challenge that within the thesis is highlighted as a possible impediment for South African domiciled banks as well. The third hurdle identified is the lack of an external data collection process among Albanian banking system participants. Allen and Bali (2004) bring to the fore an additional complexity in the use of external data and that being the lack of low frequency, high severity events which are crucial in informing the tail of the parametric distribution. Additionally, risk data gathered during an economic expansion is deemed to be unsuitable to be used during a recession.

Notwithstanding the above, Kaiser and Kohne (2006) concede that there are some expected benefits of gradating to AMA, including the elimination of regulatory arbitrage (as the capital charge is entirely based on the individual's bank risk exposure to operational losses); an increased level of flexibility in incorporating innovation in the quantification process (internal models); AMA's consideration of risk controls, diversification benefits, as well as risk transfer contracts (insurance), which effectively reduces the capital charge; that it encourages banks to improve risk management processes and procedures, and a reduced compliance cost owing to alignment between regulatory and economic capital (Regulatory Capital is calculated at a confidence interval of 99.9%, whilst Economic Capital is calculated at 99.93%). Some of the qualitative drawbacks of AMA include being able to do just as much risk management as AMA when using simpler approaches (Rebonato, 2007); the fact that only large international banks are permitted to use AMA, thus giving them unfair advantage compared to smaller competitor banks; there being no guarantee of a capital benefit post gradating to AMA, and the exorbitant development costs for the internal models. This thesis will assist in addressing the latter, as it goes into detail on the implementation of an LDA in the quantification of operational risk using AMA, and tests the potential benefit for South African banks gradation to AMA from TSA.

In a bid to demonstrate the growing importance of the ability to assess, predict, and effectively manage operational risk, El Arif, F. Z. and Hinti, S. (2014) quote some examples of the huge operating losses that have had a profound and detrimental effect on financial markets. These include Enron's US$2.4 billion cost; Allied Irish Bank's US$690 million, and Barings Bank's US$1.3 billion. The sheer magnitude of these examples is a clear indication to South African financial institutions for the urgent need to be able to define, measure and manage operational losses. A key strategy to hedge operational risk exposures is to hold capital that covers both expected and unexpected losses. Fatima Zahra El El

El Arif, F. Z. and Hinti, S. (2014) also discuss the complexities of quantifying operational risk, chief of which is the notorious lack of credible historical loss data, especially rare losses with a high severity. To further exemplify this element, a typical Poisson distribution requires a minimum of 1,082 observations, whilst a severity distribution, for example a lognormal distribution, needs more than a million points to produce an acceptable estimate (with an error margin of 5%, and a level of confidence of only 90%). In contrast to Kaiser and Kohne (2006), El Arif, F. Z. and Hinti, S. (2014) state that AMA methods lead to an *a priori* lower capital charge in comparison to BIA, and additionally state that though the gross implementation costs of AMA may be deemed as high, its marginal cost is not. In assessing BIA against TSA, traditional banks that largely deal in retail banking / brokerage would be better served under TSA as they would be charged 12% of their GI, whereas under BIA they would be charged a higher beta factor of 15%. In the instance of a traditional retail banking outfit, it is more profitable to advance to TSA, as opposed to remaining on BIA.

Valova (2011) assesses all three Basel II approaches for the calculation of regulatory capital for operational risk, focusing on the methodologies of quantifying operational risk, as well as the advantages and disadvantages of each particular method. Three methods within AMA are identified, which is an extension from the two identified by Francesco and Ardita (2012). These are the Internal Measure (International Measurement Approaches), Distribution Losses (LDAs), and Systems Indicators (Scorecard Approaches). Valova (2011) highlights that IMA presumes a linear relationship between expected losses and unexpected losses. In analysing LDA, he identifies the difficulties of combining internal and external data, with the internal data having an insufficient quantum of catastrophic losses. The solicitation of expert opinion is suggested as a plausible solution to this shortcoming. The modelling of expert opinion is beyond the scope of this thesis. The other source of complexity in the quantification of operational risk is with regard to the fact that the Basel II definition does not include all operational risks (the definition only accounts to approximately 50% of its actual size). Mention is made that AMA allows a capital benefit of up to 20% on the basis of commercial insurance, although in the Czech Republic the impact of commercial insurance has been insignificant. To emphasise the impact of operational risk losses on financial institutions, Valova (2011) lists a selected few operational risk events that have happened across the world, the largest being US$48 billion from Nomura Securities, owing to inadequate trading limits and controls. Valova (2011) found that 9.8% of the total capital requirements of the Czech banking sector was allocated to operational risk regulatory capital. The largest risk that dominates the Czech banking sector is Credit Risk, to which 88% of the sector's regulatory capital is allocated to. A crucial weakness relates to the possible bias that could emanate from the expert opinion that is fused on to historical loss data – for example, where management may have the tendency to overestimate the quality of its management, owing to possibly poorly determined remuneration structures.

Sundmacher (2004) takes to task the use of GI as an operational risk indicator as used in TSA and BIA, and discusses alternative leading indicators at length. Though the subject matter may not talk to the direct gradation from TSA to AMA, some of the pertinent issues of this article that relate to this thesis are highlighted here. The decision as to which quantification method to opt for is viewed as a cost / benefit trade-off between the developmental costs, the data collection, and collation costs, against the benefits of regulatory capital relief. Again in this article as in that of Sundmacher (2007), the issue of a bank's structure being a major influencing factor between the two alternatives comes to the fore. A note is made that neither of the simplistic options will result in a capital relief on the basis of commercial insurance, diversification benefits or contingency plans. Sundmacher (2004) alludes to the fact that trading volumes may be a more suitable indicator of operational risk than GI. In direct contradiction to Sundmacher (2004), the BCBS justifies its choice of GI as the ideal operational risk indicator (for BIA and TSA), owing to its simplicity, comparability, reduction of arbitrage possibilities and a lack of evidence of greater risk sensitivity of other indicators. Sundmacher (2004) concludes by highlighting the grave possibility of gaming under both BIA and TSA [See also collaborative sentiments from Synman (2011)].

Laycock (2014)'s paper focuses on AMA models, and in particular their data requirements, the link to risk management, and issues surrounding their implementation. The novel elements that he brings to the fore are: identification of the fact that data collection, storage and analysis infrastructure costs are a key hindrance to a bank's migration from TSA to AMA; and that in the case of TSA and BIA the only way to reduce the risk estimate is to earn less GI, an objective which would not sit well with any of the stakeholders of the business. Some of the complexities he identifies relating to the management and quantification of operational risk is the difficulties in reverse engineering the components that make up the AMA quantum. For Credit and Market Risk it is possible to determine each risk factor that makes up the ultimate VaR. In Laycock (2014)'s conclusion, he takes cognisance of the cons surrounding AMA, but is of the opinion that despite these, AMA models are still preferable to TSA and AMA, especially in relation to risk sensitivity and risk management support. Also of interest, on a technical detour, is his identification of the challenges of using a directly observable value from an ALD at 99.9% confidence level. Difficulties in validation, and possible volatility as a result, is mentioned, and it is suggested that a lower value for a lower confidence interval possibly be taken, and then possibly scaling it up to produce a value equivalent to the 99.9% confidence interval demanded by the regulators [this translates to conceptualising the 1 in 20 year event, which is a far better bet than trying to conceptualise a 1 in 1000 year event]. This approach is not new *per se*, but has been borrowed from Market Risk, where a scalar of 3 has been used.

Kaiser and Kohne (2006) concur with Francesco and Ardita (2012), and identify a fundamental problem with the Basel II's premise of thought that financial institutions that move on to AMA, are rewarded with a lower regulatory capital charge. The problem is the AMA assumption that the summation of high percentiles of VaRs is an ideal indicator of the inherent operational risk within a bank. This by inference means that the worst possible outcomes occur simultaneously, which in reality is hardly ever the case. Added to this, should the assumption of perfect correlation across Operational Risk Cells (ORCs) be assumed valid, then the capital charges of the various ORCs should be summed, and in the process effectively resulting in a higher capital charge than that determined by the simpler approaches. Kaiser and Kohne (2006) conclude, in agreement with Nash (2003), that financial institutions should not take it as a given that changing to AMA will definitely result in a capital benefit, but should rather explore all available quantification methodologies in a bid to identify the ideal method that takes the idiosyncrasies of the particular bank into account. This view coincides with the findings of Sundmacher (2007), who used a hypothetical example to show that the capital benefit (if at all) depends on a financial institution's distribution of its GI. In his specific example, he found that the incentive to move from BIA to TSA is non-existent, or marginal at best. In the following part of the chapter, I look at prior literature on operational risk modelling approaches under the ambit of AMA.

2.2.1 Prior research on AMA modelling approaches

Afambo (2005) investigates the implications of AMA in operational risk capital quantification within a Basel II and US regulation paradigm. The AMA model developed in this article uses LDA and Extreme Value Theory (EVT) to quantify operational risk. Four quantification methodologies are identified, and these being Probabilistic approaches, Fixed Ratios, Risk – Based Capital and Scenario Based approaches. Probabilistic approaches such as AMA though convolute are regarded as being superior to their counterparts largely on the basis of their use of simulations to ascertain the probability distribution that best describes the possible outcomes[13]. The assumed intrinsic design behind Basel II quantification methods that being AMA should provide a capital reduction incentive ahead of TSA, and BIA is brought to question[14]. This skepticism is supported by the results of a survey carried out by Fitch in 2004, wherein forty two banks from around the world also expressed their support of the view that is was possible that BIA and / TSA could generate a regulatory capital charge that was lower than that quantified by AMA (Fitch, 2004). The additional criticism against AMA is the use of EVT and LDA to appropriately capture the peculiar nature of operational risk. The assumptions behind EVT and LDA are regarded as being at logger heads with the actual attributes of operational risk. (Embrechts, Kaufmann, and Samorodnitsky, 2004). Afambo (2005) identifies a pervasive problem that has not been appropriately highlighted by other scholars, and that being that most models are by design and intent

[13] KPMG. (2002). Commission services study prepared by KPMG on the methodologies to assess the financial position of an insurance undertaking from the perspective of prudential supervision. Preprint, European Commission, http://europa.Eu.Int/comm/internal_market/insurance/docs/solvency/solvency2-study-kpmg_en.Pdf.
[14] http://archive.financialexpress.com/news/fitch-sees-hitch-in-basel-operational-risk-rules/103362

more appropriate for larger data pools. This underscores the need for empirical studies that take cognisance of the varied hurdles in the quantification process, namely limited data, computational resources and decision time. The empirical investigations carried out by Afambo (2005) make use of public data from Fitch Risk Management for the period 1980 to 2002. The public data had a collection threshold of US$1 million, and mainly comprised of banks (1,245) and insurance (381) companies. This is in direct contrast to this thesis empirical research which makes use of privately held data of a South African domiciled bank. The use of a single bank's ILD set evades issues faced by Afambo (2005) relating to the need to assess the appropriateness or lack thereof to treat the contributing bank's truncation point as a constant and a known. In the case of this thesis, the truncation (discussed in section 2.6.1.1) is a known (R10, 000), and constant. Thus the key challenges of empirical research based on public data is the unknown truncation point (referred to as a reporting bias), and scaling issues owing to different sized banks contributing to the data set. Afambo (2005) uses Random truncation modelling that assumes a logistic distribution to address the reporting bias. In his article, he further affirms our use of the Poison distribution to model the frequency of loss occurrences. In modelling dependency structures, a Student's T - Copula approach is used.

The conclusive findings that have relevancy to this thesis are: the results indicated that in the instance that a constant and known truncation point is assumed (as is the case in this thesis), the resultant severity parameters were found to be higher than the alternative, wherein a logistic distribution is assumed. The thought behind this observed phenomenon was that the case of the assumed known and constant truncation point ignores the inherent reporting bias within the data, and thus assigns equal weighting to all losses. The overall impact of this total disregard of the reporting bias, resulted in higher levels of regulatory capital. The remaining distinctive difference largely remains that Afambo (2005)'s use of public data with varying contributors, giving rise to the reporting bias. Whereas, in this thesis, the contributor is a singular entity, whose data collection thresholds, as well as the truncation points are known constants. Thus the higher capital charge observed by Afambo (2005) is unlikely to be a factor within the results of this thesis. The riskiest event type within the Fitch data set analysed, was CPBP and IF and in particular in the investment banking space (which were found to drive regulatory capital). For model selection, the Akaike Information Criterion (AIC) was used as is the case in this thesis (see addition detail on the AIC on section 2.6.3.1). However, in contrast the Kolmogorov – Smirnov and Anderson Darling tests were not performed, reasons of which are detailed in Moscadelli (2004). Afambo (2005) found that if one is using Cauchy or Student's T – Copula, the savings range for banks levelled out at 6% to 10%. The ultimate capital results attained in this research article are in line with other prior research, and would seem to validate the random truncation assumption (on the back of appropriately calibrated scaling mechanisms or methodologies). This paper is one of the few articles that tries to be appropriately comprehensive enough on an end to end basis, touching on stochastic truncation model, EVT and copulas, some of whose ideas have been used as building blocks in this thesis (as shown in the technical review).

Synman (2011) investigates the development of an end to end operational risk quantification model touching on all key building blocks (data analysis, capital calculation and allocation), in a case study format. The main driver and justification for his article is the realisation of a lack of a comprehensive best – practice approach to quantifying operational risk under AMA irrespective of the succinct guidance notes detailed by BCBS 2009, and 2011b. The novel elements that he brings to the fore are: the importance of selecting the desired level of granularity, as a too granular a level may lead to distributional split and scarcity of data whilst the alternative may lead to over – fitting and parameterisation of data. The BCBS (2009)'s range of practice survey found that most banks had 20 to 60 operational risk classes (ORC). The level of granularity chosen may also have bearings on capital allocation process, and the Use Test (both of which are out of scope of this thesis). Synman (2011) specifically uses EVT, thus the choice between light – tailed and heavy tailed theoretical distributions to model severity, determination of the optimal truncation points and thresholds is also of vital importance. The light tailed distributions considered were: Beta; Chi – Square; Exponential; Gamma; Inverse Gaussian; Lognormal; Normal; Weibull and Rayleigh. The heavy tailed distributions considered were: Burr; Cauchy; F; Generalised Pareto Distribution; Generalised Extreme Value Distribution; Log Gamma; Log Logistic; Pareto; Student T [additional context can be read from (Mignola and Ugoccioni, 2006)]. Notwithstanding the fact that for this thesis only, four of the eighteen distributions mentioned by Synman (2011) were utilised, the four are sub-exponential distributions that adequately estimate the tail properties of the empirical data. It is worth noting that as per the Basel Committee's paper on Range of Practices (BCBS160b) 31% of the AMA banks apply a single distribution model to all the data with the Lognormal and Weibull being the most widely used distributions. The Lognormal is used by 33% of the AMA banks while the Weibull is used by 17% of the AMA banks – half the banks applying the single distribution model for all the data use as is the case in this thesis. Having stated which theoretical distributions are largely used for modelling loss severities, Synman (2011) depicts the Poisson, Geometric and Negative Binomial as those that can be used to model loss frequency. However, there is an overwhelming amount of empirical and literature from the likes of Mignola and Ugoccino (2006), De Fontnouvelle, P., Rosengren, E. and Jordan, J. (2004) and BCBS (2009) that advocates for the use of the Poisson Distribution in describing the loss occurrences over a sustained period of time.

The tests and graphic plots commonly used to ascertain the above elements are: Tail Plot; Mean Excess Plot; Hill Plot Estimator; Huisman, Koedijk, Kool and Palm Plot; Stability Parameter Plot and finally the Dekkers, Einmahl and de Haan plot. Various distribution fitting methodologies are discussed, namely Maximum Likelihood Estimation (MLE), Least Squares (LS), Probability Weighted Least

Squares (WLS), Robust Least Squares (RLS) and Method of Moments (MoM). For this thesis, MLE, and WLS were used to determine the fit for the ILD, and Scenarios respectively, whilst the EVT tests, and graphic plots where not performed. In operational risk the quality of fit has a considerable impact on the ultimate capital charge, the following Goodness of Fit (GOF) tests were applied: Kolmogorov Smirnov (KS); Cramer von Mises (CM); Anderson – Darling (AD); Analysis of fit difference and Evaluation of Probabilities and Quantities. In this thesis I discuss, and perform the KS, CM and AD (these are mentioned as being most significant for evaluating theoretical distributions). Synman (2011) makes no mention of the Chi Square test and the Mean Square Error (MSE), on the basis that these are not commonly used in practice, and their inherent limited sophistication in comparison to the other GOF tests mentioned. The GOF tests discussed are largely numerical technics, but to complement these graphical GOF tests are available and extensively discussed in Dutta and Perry (2006). Synman (2011) lists the following as being commonly used: Probability Differences Plot; Probability – Probability Plot (PP Plot) and Quantile – Quantile Plot. To understand the interdependence structures between the business lines and / or event types dependent simulation of the copulas was used (in particular the Gaussian copula). Synman (2011) gives both the methodology of calculating Diversified VaR, and Stand-alone Var. The Stand-alone VaR assumes that all ORCs are 100% correlated (full dependence), an assumption held in this thesis. In analysing his findings, the retail and investment banking sections of the bank had the highest allocations of capital, as these two are understood to have the highest overall risk exposure. The other supporting business, and other smaller frontline business units with limited scale, complexity and scope also reflected a lower regulatory charge as per expectation. Similar trends were evident with regard to Expected Loss (EL). The retail business had the highest EL, as it had frequent lower value losses; whereas the investment banking arm had a far lower EL, as the losses they face are high impact low frequency losses. In his comparison of AMA and TSA's ultimate calculations, he observes that beta factors for TSA would seem to be wrongly calibrated as their application seems to be at loggerheads to the inherent operational risk. Additionally, he finds that the individual business unit regulatory capital proportions are approximately the same as those of EL under TSA, indicative of an anomaly within TSA beta factors. In the following part of the chapter, I look at prior literature as well as a technical review on operational risk quantification under the ambit of TSA.

2.3 The standardised approach (TSA) [Technical Review]

The BCBS proposed two operational risk quantification methods that are premised on a financial institution's GI. These are the BIA, and the TSA. GI is defined as net interest income + net non-interest income (BCBS, 2006). Sundmacher (2007) highlights that the income figure is gross of operating expenses, provisions, income from insurance, realised profits or losses from the sale of securities in an institution's banking book, and any irregular items. Additional insights on the building blocks and the mechanics of the BIA, as well as the eligibility criteria for a financial institution to use the TSA are detailed in (BCBS, 2006). In TSA banks are called upon to map or atlas their overall annual GI into business lines that are predefined by BCBS. TSA is marginally granular in comparison to BIA in that the GI is scaled by a BCBS predefined beta factor (whereas in BIA operational risk capital is calculated as a fixed percentage of an annual three year average positive GI). The beta for each business line is pre-determined by the BCBS, and its magnitude is said to be largely dependent upon a business line's riskiness (Fatima and Said, 2014). BCBS (2006) identifies the following business lines and their respective betas as illustrated in Table 2.1:

Table 2.1: Business lines and their betas[15]

Business Lines	**Beta Factors**
Corporate Finance	18%
Trading and Sales	18%
Retail Banking	12%
Commercial Banking	15%
Payment and Settlement	18%
Agency Services	15%
Asset Management	12%
Retail Brokerage	12%

The total capital charge using the TSA is attained by summing up the underlying business lines' capital requirements. This is mathematically articulated in the following manner (BCBS, 2006):

$$K_{TSA} = \{\sum_{years 1-3} \max [\sum (GI_{1-8} * \beta_{1-8}), 0]\} / 3 \qquad (2.1)$$

The above formula calculates the total operational risk capital charge by taking the GIs for the eight business lines in Table 2.1, and multiplying them by their respective beta factors. In cases where there is a negative GI, a zero value is used. The mathematical product of GI and the respective betas for each of the business lines are summed for the past three years, and an average is obtained by dividing by three, which gives us the operational risk capital charge using the TSA model. Sundmacher (2007) highlights as key differentiator between BIA and TSA that an overall reduction in the capital charge may be attained when a negative GI of one business unit or line is offset against another, whereas in the BIA no such liberties are permitted. Sundmacher (2007) concludes that, notwithstanding the setoff

[15] Source: BCBS (2006)

afforded by TSA, the overall capital charge cannot be negative and hence lead to a setoff against market or credit risk capital levels.

2.4 The advanced measurement approach [Technical Review]

Of the available operational risk quantification methods, the most erudite approach is the AMA. The AMA gives banks free reign to choose an idiosyncratic quantification methodology, this thought is premised on providing banks with the platform to innovate the quantification / measurement process as they deem fit. The full details of this rationale are detailed in BCBS (2001). In this section I focus on the key pillars for a robust AMA modelling program.

The SARB regulations and BCBS (2006) define requirements for operational risk management from both a qualitative and quantitative perspective. The Basel II regulatory guidelines for the AMA state that capital should be calculated using appropriate quantitative and qualitative criteria (see also sections 1.2.1 of this thesis). The recurrent and stable losses that can be predicted are referred to as expected losses and the rare large loss events that are out of the norm losses are referred to as unexpected losses (Fatima and Said, 2014). In the regulatory capital context, the unexpected loss is the deviation above the mean at a specified confidence level, whilst the expected loss (EL) is the arithmetic mean of a loss distribution, as shown below (BCBS, 2006; Moscadelli, 2004).

Figure 2.1: Cumulative loss distribution[16]

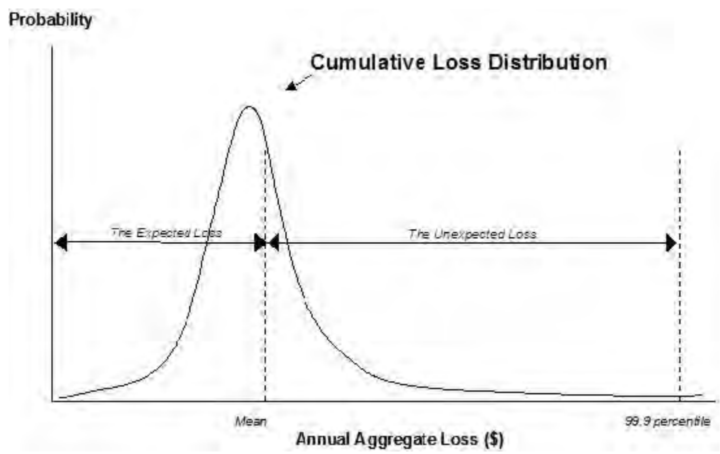


Figure 2.1 provides a diagrammatic view of unexpected and expected losses (at the 99.9% confidence level for a 1-year holding period). It details the fundamentals of operational risk modelling, highlighting that an Aggregate Loss (AggL) Statistic; an Expected (aggregate) Loss (EL) and VaR are defined as

[16] Source: Shevchenko (2011)

EL = mean (AggL) and $Var_{\alpha} = \inf \{I € R: F_{AGGL}(I) \geq \alpha\}$. VaR at the confidence level α is given by the smallest number *I* such that the probability that the (AggL) exceeds *I* is at least α. That is, it is in the (1 – α) th percentile (Shevchenko, 2011). Basel II regulatory guidelines for AMA states that a bank needs to show that its operational risk quantification approach has taken cognizance of 'tail' loss events (at a 99.9 percentile confidence interval) within a one year holding period (BCBS, 2006). The use of VaR in measuring the regulatory capital requirement aligns with this requirement, as the time period and a confidence level are amongst the important components of defining a VaR. (Shevchenko and Wuthrich, 2006).

2.4.1 Data used in AMA modelling

A financial institution that intends on adopting AMA is required by the regulations to demonstrate the use of the key data aspects in order for it to meet the supervisory soundness standards (BCBS, 2006). These data elements include ILD, external loss data (ELD), scenario analysis, and factors reflecting the business environment and internal control systems (BEICFs). These data elements may be used as direct or indirect inputs into the model. BEICFs are informed by risk control and self-assessment (RCSA), together with the key risk indicators (KRI) (BCBS, 2006). Measuring operational risk requires historical loss data. However, most South African banks do not have much ILD, a problem that is pervasive across the world (as detailed in the first section of this chapter). In addition, since operational risk distributions have "long tails", in order to accurately measure the probability of loss in the tail region one needs an extensive quantum of data (BCBS, 2006). The amount of data required depends on a number of factors. Two of the most important factors are whether the data are independent and identically distributed (i.i.d.), and the volatility of the underlying distributions. If the data is not identically distributed, then it must be in sufficient amounts to represent each class of exposure available for modelling. As highlighted in BCBS (2006), there are two types of historical loss data, ILD and ELD, which is briefly discussed below.

2.4.1.1 Internal loss data

ILD of a minimum of five years needs to be collated if it is to be part of operational risk VaR capital calculations. The data must contain all notable activities and exposures, with a possible loss collection threshold being imposed. The information collected must be complete with regard to gross loss amounts, date of event, recoveries, and anything that will assist with the identification of the cause or drivers of the event (Shevchenko, 2011). Full details on supervisory guidelines regarding ILD for AMA can be found in BCBS (2011). In the same year, BIS published a paper providing operational risk data and practices of institutions implementing Basel II, the observed range of practice in key elements of the AMA (Range of Practice Paper)[17]. Some of the key findings were that the absence of definitions for "gross loss" or "recoveries" from the regulators, and the differing data capturing practices among banks, resulted in differences in the loss amounts recorded for similar events, leading to potentially massive discrepancies in banks' respective capital calculations (BCBS, 2011). The differing practices was substantiated by the fact that, for example, 42 participating AMA banks (43%) modelled on a "gross loss after all recoveries" (except insurance), whilst "gross loss before any recoveries" was used by 29%, "net loss" was used by 14%, and the balance of 12% used "other definitions" (BCBS, 2011).

2.4.1.2 External loss data

There are three types of ELD, public data, consortium data and insurance data (not discussed in this thesis). This type of industry data that is available from external databases has some key draw backs which Lambrigger, Shevchenko and Wuthrich (2006) discuss at length. The chief drawback these authors highlight is that it is problematic to adjust the data to processes within a respective bank owing to differing thresholds, volumes, etc. In an earlier study by Shevchenko and Wuthrich (2006), it is argued that external data tends to suffer from survivorship bias. Public data is largely information that is sourced from publicly available pools, the likes of newspaper reports, legal judgments etc. Public data sets normally have a strong size-based reporting bias making it difficult to extract severity and frequency parameters from it (Shevchenko and Wuthrich, 2006). This data is ideally used in practice in different forms; from building scenarios to benchmarking correlations (in the calculation of diversified capital). Consortium data are pooled sets of internal data submitted by member organizations such as, for example, the Operational Riskdata eXchange Association (ORX). ORX is dedicated to advancing the understanding of operational risk with respect to financial services industry[18]. It collects operational risk loss events from its members, all of whom are banking institutions, through the ORX Global Loss Database. The threshold for the operational risk losses submitted to the consortium by its members is €20,000. Consortium data is not subject to public (media) reporting biases[19] (Shevchenko, 2011). The key challenge for African domiciled banks is likely to be the fact that such consortiums are largely made up of large international banks that reside and operate outside Africa, with only four members from Africa (being part of the ORX association). This gives rise to the need to devise a scaling tool that will take into account the varied inflations, currency, GDP parities before that data may be deemed useable (see also Afambo, 2005).

[17] www.bis.org/publ/bcbs160.htm.
[18] https://www.orx.org/Pages/HomePage.aspx
[19] Major issues with External data are to do with the use of different volumes and other factors, chief of which is survival bias as data of all collapsed banks is not available.

2.5 Modelling operational risk

Frequency refers to the number of events that occur within a given time period. In an actuarial model, frequency is stochastic and has to be expressed as a probability distribution. Naturally, the state space for the frequency distribution should be a subset of all non-negative integers. Empirical evidence suggests (BCBS, 2006) that operational loss frequency can be modelled using one of the following: the Poisson distribution, the negative binomial, or the binomial distribution (not discussed in this thesis). The Quantitative Impact Study 4 (QIS-4)[20] submissions showed that many of these distributions were reported as used by financial institutions (De Fontnouvelle, Rosengren and Jordan, 2004; Dutta and Perry, 2006).

2.5.1 The Poisson distribution

Frachot, A., Moudoulaud, O. and Roncalli, T. (2003) highlight key characteristics of the Poisson distribution, which are its one-parameter distribution; the mean and variance of the Poisson distribution are both equal to λ. The sum of two independently distributed Poisson random variables is still a Poisson random variable, with its mean parameter being the sum of the means of the two component distributions. In actuarial modelling, the Poisson distribution is preferred in modelling because of inherent analytical qualities as mentioned above (De Fontnouvelle *et al*., 2004). This was also confirmed and applied by Mignola and Ugoccioni (2006) and Dutta and Perry (2006).

2.5.2 The negative binomial distribution

The key referral article for this section is Moscadelli (2004). The Negative binomial is an alternative to the Poisson distribution when the observed mean of the losses being considered is less than the observed variance of the considered losses. The negative binomial distribution arises from a series of Bernoulli trials that is, having a series of random events until a possible outcome can occur (usually denoted success or failure). In practice, if there is variability in the frequency, then the best alternative is to use the negative binomial distributions as compared to the Poisson distribution. The negative binomial distribution is also more flexible when compared to the Poisson distribution, since it has two parameters. If some volatility is introduced to the mean parameter of the Poisson distribution, a negative binomial distribution is attained (hence, as the volatility gradually dies down, the distribution moves towards a Poisson distribution, in the limit).

[20] http://www.bis.org/bcbs/qis/qis4.htm

2.6 Modelling severity

De Fontnouvelle *et al*. (2004) and Dutta and Perry (2006) identify prevalent methods for fitting the severity distribution, i.e. Exponential, Lognormal, Lognormal-gamma, Log-logistic, Weibull, Generalized Pareto, and g-and-h distributions. Notwithstanding that there are numerous distributions which one can consider in modelling severities, in this study the only considered distributions in modelling the loss severities are the Lognormal, Weibull, Burr, Generalized Pareto and Gamma distributions. These were deemed to be more stable (Dutta and Perry, 2006). Additionally, they can be used with small samples (from 25 data points and above).

The lognormal distribution is a continuous probability distribution of a random number that has a normally distributed natural logarithm. Thus a positive random variable $X = (x_1, x_2 \dots x_n)$ follows a lognormal distribution if $Y = (y_1, y_2 \dots y_n) = (ln(x_1), ln(x_2) \dots ln(x_n)) = ln(X)$ follows a normal distribution. The Burr distribution is a three – parameter distribution. It is less stable but more flexible, and requires at least 100 data points to be used safely. It can be used to model fat tail distributions when necessary. The use of many of these distributions for operational risk severity modelling was also proposed and detailed by Mignola and Ugoccioni (2006). The probability density functions (pdf) and the cumulative distribution functions (cdf) of the distributions considered in this study are discussed by Dutta and Perry (2006).

2.6.1 Distribution fitting

Operational loss data is almost always collated beyond a certain threshold (data truncation – see BCBS, 2006). This presents a challenge to modeling loss severity, as most loss severity distributions were developed to model data sets where there is no threshold (*i.e.* where the data is collected from the ground up), except for a very few well-defined distributions that were developed to model truncated data sets (such as the Pareto distribution). These distributions cannot be used in their original form to fit truncated data. One plausible analytic solution to resolve this problem is maximum likelihood estimation (Ergashev, 2008).

2.6.1.1 Maximum likelihood estimation

Ergashev (2008) compares the maximum likelihood estimation performance against three other estimation methods that can be used in fitting operational risk models to loss data. Maximum likelihood estimation (MLE) is a process used to fit empirical data to a theoretical distribution. Given a pre-specified theoretical distribution, MLE is used to ascertain the set of parameters which have the maximum likelihood (probability) of describing the empirical data set. In most instances, the likelihood function is the density function, however in instances where loss data is truncated, an adjustment is required. Ergashev (2008) highlights that the typical collection threshold is in some instances set as high as US$10,000, and sometimes even higher, whilst Shevchenko and Wuthrich (2006) quote US$20,000 for this threshold (see also Frachot *et al.*, 2003 for a detailed rationale on the inverse relationship between an increase in collection threshold leading to a deep in the capital charge). However, in this thesis I do not delve further on the underlying reasons for such thresholds, except to highlight that in operational risk, left truncated data is a norm (Baud, Frachot and Roncalli, 2003). The latter authors largely attribute this to loss collection thresholds and/or insurance deductions from the losses. The underestimation of parameters leading to underestimation of capital is largely due to fitting a probability distribution to the truncated data, and not adjusting for the imposed truncation point (De Fontnouvelle, De Jesus-Rueff, Jordan and Rosengren, 2003).

De Fontnouvelle *et al.* (2004) argue that the MLE method is arguably the most frequently used estimation method in current operational risk capital quantification practice. However, Ergashev (2008) highlights that MLE matching accurately measures the bodies of empirical and fitting distributions where the likelihood mass is concentrated. Ergashev (2008) reports that for small amounts of data, Quantile Distance Method leads other estimation methods, including the MLE, and concludes that the reason for the superior performance is due to the Quantile Distance Method focusing on fitting high level quantiles, which are more precise estimators of capital. Additionally, Shevchenko (2011) concludes that MLE is indeed useful and widely used, but that is has a drawback, namely that asymptotic approximations are in most cases not accurate enough in instances where the data is limited, resulting in the distribution of parameter errors that are materially different from normal (hence MLEs may have significant bias). The other challenge which is common to all asymptotic results is that when using MLE one cannot precisely identify a sample size that is large enough on which to use the asymptotic approximation.

2.6.2 Statistical goodness of fit tests

Goodness of fit (GOF) tests are essentially for comparing the fitted distribution to the empirical one. This is largely a standard semiparametric procedure to assess the level of distribution fit. For this section the tests and their computation referred to, are drawn from Chernobai, Rachev and Fabozzi (2012). Lavaud and Leherisse (2014) analysed selection methods, paying particular attention to the mainstream properties of these methods used in the LDA. The different distributions considered in this dissertation are narrowed down through choosing the one that fits the data best for each business unit and/or risk category. The criteria for such a choice are based on some kind of measures of GOF. There are several recognized statistical tests for measuring the GOF. These methods are used to diagnose the quality of fit between the data and an estimated distribution. These tests are used for hypothesis testing, essentially rejecting or accepting a distribution subject to certain critical values. The respective GOF tests calculate a score for a respective distribution, which measures the "overall" difference between the empirical distribution and the chosen distribution. In the instance that the score exceeds the critical value, the null hypothesis is rejected, essentially implying the empirical data comes from the distribution in question. However, if the score is less than the critical value, this suggests that there is no strong evidence to reject the null hypothesis (Moscadelli, 2004). The minimum standards relating to GOF tests are found in BCBS (2006).

2.6.2.1 The quadratic Anderson-Darling test

Anderson and Darling (1954) pioneered the quadratic Anderson Darling (AD) goodness of fit test. The quadratic Anderson Darling (AD) test is derived from the Cramer–von Mises test, and it essentially confers a greater weight to the left and right tails of the distributions than to the body (Lavaud and Leherisse. 2014). This means that it puts more weight towards the end regions, and therefore emphasizes the tail-end fit, resulting in this test being most appropriate for models that depend on the tail-end precision (chief of which is the VaR calculation). For a candidate distribution with F_{cdf} and a set of n empirical loss observations, the Anderson –Darling test is calculated using the formula:

$$T_{AD} = - n - \sum^{(2i-1)/n} [\text{In} (F (x_i)) - \text{In} (1 - F (x_{n+1-i}))] \qquad (2.3)$$

Where n is the total number of observations, and x_i*'s* are the observed empirical data arranged in a non-decreasing order: $x_1 \leq x_2 \ \ldots.. \leq x_{n..}$ Note that the Anderson Darling (AD) Test is extensively discussed in Panjer (2006) and applied by Mignola and Ugoccioni (2006) and Ergashev (2008).

2.6.2.2 The modified quadratic Anderson-Darling test

The modified quadratic AD (ADup) test is based on the same principle as the basic AD Test, but has a different weighting, which confers a greater weight to the right tails of the distributions (*i.e.* the biggest losses / high severity) (Lavaud and Leherisse, 2014). The modified quadratic Anderson-Darling test is generally deemed as being more demanding than the Kolmogorov-Smirnov or Cramer von Mises tests (Dutta & Perry, 2006) and is presented as follows:

$$AD_{UP} = - 2n \text{ In} (1 - z_t) + 2 \sum \text{In} (1 - z_t) + (1 - z_t) / n \quad \sum 1 + 2 (n - j) / 1 - z_j \qquad (2.4)$$

2.6.2.3 The Kolmogorov-Smirnov test

The Kolmogorov-Smirnov (KS) test measures the differences between the empirical and theoretical distributions at the point *x* where the fit is the worst [encapsulated in the use of the max in the formula below] (Moscadelli, 2004). It is thus a local test (Lavaud & Leherisse, 2014). The KS test, extensively discussed by Panjer (2006), is calculated as follows:

$$T_{ks} = max_{\,1 \leq I \leq n} \,|\, F\,(x_i) - {}^{1}/\, n \,| \qquad (2.5)$$

Where *n* is the total number of observations, and x_i*'s* are the observed empirical data. One of the good features about the KS test is that the distribution of T_{ks} under the null hypothesis is independent of *F*. It can be shown that T_{KS} always observes the same distribution (for fixed sample size *n*) under the null hypothesis. The problem is that this property can also lead to the test being likely to accept wrong models (prone in small sample sizes) (Knuth, 1998). As a measure of goodness-of-fit, the KS test does not put emphasis of the fit on any specific sub-range of the distribution, and therefore it is generally viewed as a measure of overall fit. A given theoretical distribution ranked as the best by the KS test may not fit, say, the tail-end region as well as some other distributions. This test was, amongst other, used by Mignola and Ugoccioni (2006), and Dutta and Perry (2006).

2.6.2.4 Cramer-Von Mises test

The quadratic Cramer–Von Mises (CvM) test measures the mean square deviations between the empirical distribution and the estimated distribution, with the same weighting for each observation (Lavaud and Leherisse, 2014). For a candidate distribution with F_{cdf} and a set of *n* empirical loss observations, the Cramer-Von Mises test is calculated by the following formula:

$$T_{CVM} = {}^{1}/\, 12n + \sum [\, {}^{2i-1}/\, 2n - F\,(\, x_i\,)\,]^2 \,| \qquad (2.6)$$

Where *n* is the total number of observations, and x_i*'s are* the observed empirical data arranged in a non-decreasing order: $x_1 \leq x_2 \; ..... \leq x_n$. The Cramer-Von Mises test thus aims at minimizing the overall difference between the empirical distribution and theoretical (see Mignola and Ugoccioni, 2006, for additional insights).

Table 2.2: Statistical goodness of fit tests advantages and disadvantages

Test Name	Advantages	Disadvantages
Kolmogorov-Smirnov	Not dependent on how loss data is binned Tables for critical values and associated cumulative probabilities are widely available True distribution (null hypothesis) more likely to be confirmed by the test	Restricted to continuous distributions The tail is less sensitive compared to the centre of the distribution. Not a very powerful test: it has less power in detecting evidence of violation of the hypothesized
Anderson-Darling	Not dependent on how loss data is binned Sensitive to the distribution in calculating critical values Emphasizes the fit of the tail of the distribution	Restricted to continuous distributions Tables for critical values and associated cumulative probabilities are only available for select distributions since it depends on the actual distribution under test.
Cramer-Von Mises	Not dependent on how loss data is binned	Restricted to continuous distributions Tables for critical values and associated cumulative probabilities are not available.

2.6.3 Modelling distribution selection

Of the distributions that are considered in modelling severity, at least two distributions can pass the GOF test. An extra tool to support the model selection process is the Akaike information criterion (AIC).

2.6.3.1 Akaike information criterion

BCBS (2006) points out that though diagnostic tools such as those discussed in previous sections provide a view on the quality of fit between the data and each distribution, there are instances where no conclusive decision is given regarding which of the proposed distributions is the ideal. Additionally, the BCBS (2006) highlights that GOF tests are considerably sensitive when it comes to sample size and the number of parameters being estimated. In the instance that the GOF tests are unclear on the ideal distribution, the BCBS recommends that financial institutions consider selection methods that use the relative performance of the distributions at different confidence levels. The named examples of selection methods in the text are the Akaike Information Criterion, Likelihood Ratio, the Schwarz Bayesian Criterion, and the Violation Ratio (BCBS, 2006).

The AIC selects a model that minimizes the Kullback-Leibler distance (which will be zero if the model and data are identical) between the model and the actual data set. The criterion selects the model that best fits the data with the least possible number of parameters (Robert, 2001). In the general case, the AIC is;

$$AIC = 2k - 2 \ln (L) \quad | \qquad (2.7)$$

k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model (Afambo, 2005). Thus, AIC rewards goodness of fit and penalties that increase with the number of parameters. Over fitting is discouraged in this way (Tsai and Hurvich, 1988).

2.7 Scenario analysis

Shevchenko (2011:112) defines scenario analysis as a process where senior management analyse past events experienced within the bank and by other banks (including near miss losses), identify risks that are idiosyncratic to the risk profile of the bank, as well as consider current and planned controls in the banks, etc. Scenario analysis permits the completion of two objectives, which are to estimate the VaR through quantifying expert opinion when loss data is insufficient or unstable to provide sufficient, accurate and reliable VaR, and to independently validate the EL, UL and VaR estimates that have been produced through a loss data based model. For this purpose, they allow validating the forward-looking aspect of the LDA (BCBS, 2006). The former objectives are usually accomplished by estimating the shape of the frequency and severity distributions (Shevchenko, 2011).

2.7.1 Scenario analysis fundamentals

This section heavily relies on the seminal work by Shevchenko (2011). The ILD profiles of most institutions show that banks do not have enough losses that can have major impact[21]. Scenario analysis addresses this, while also trying to be forward looking in terms of these major risks. The main objective of scenario analysis is to obtain a precise and distinct quantification of major risks that have been identified. This focuses on major risk events identified in Risk Control and Self–Assessments (RCSA), ILD analysis, and ELD analysis. The output of this process needs to make business sense after it has been processed using internal models. The output of this process includes the estimates of frequency and severity distributions that will be processed in internal modelling.

[21] www.bis.org/publ/bcbs160.htm

Because the frequency and severities of these losses over the next year is unknown, it is prudent to do a Monte Carlo simulation when building an aggregate loss distribution (Shevchenko, 2011). The challenge is that there is no prior knowledge that exists to allow one to strictly set the frequency at one, and to extract the 99.9 percentile from the most appropriate severity distribution. Hence, by building an aggregated loss distribution using the Monte Carlo simulation method, it is possible to address this uncertainty and have some conservatism should things be worse than anticipated by the experts. The Monte Carlo simulation provides a layer of conservatism compared to when the VaR is extracted directly from the parametric distribution (Frachot *et al*., 2003).

2.7.2 Scenario analysis modelling

The experts' estimations need to be transformed to a loss distribution that will give a capital measure at the 99.9% confidence level (similar to the 1 in a 1000 years extrapolated estimate, over a one-year holding period). The methodology used to convert the experts' subjective distribution to a distribution highly depends on the methodology used to elicit the data from the experts. These methods range from the fixed percentile, fixed quartiles and the duration approach. Only the duration approach will be discussed here (see Frachot *et al*., 2003).

- **Duration approach**

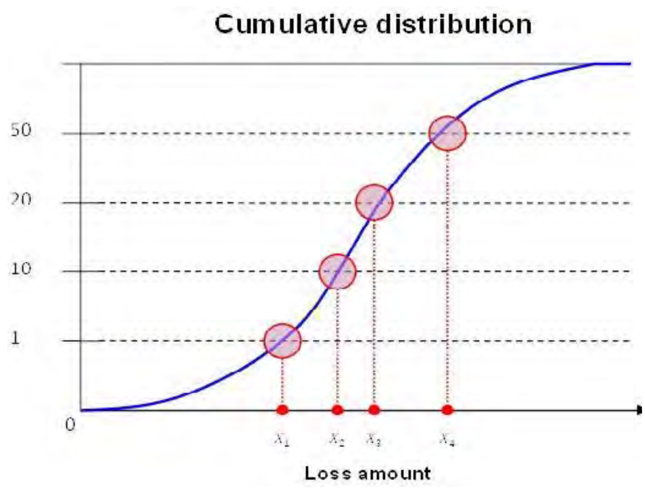
Frachot *et al*., (2003) introduced a methodology of using durations, which was later improved by Alderweireld, Garcia and Léonard (2006) to ensure that it relates to business, and can comfortably be employed by experts. The same methodology (with some variation) was also described by Peters and Hübner (2009), and Steinhoff and Baule (2006). The end result of this method is similar to that of the fixed percentile or quartile. The aim is to build a subjective loss distribution with potential loss amounts, with probabilities based on business experts' intuition, their experience and understanding of the business. The difference between this methodology and the other two is that, it allows for the information to be elicited in a more qualitative and easy to understand method to the business experts. This allows for elicitation of information that is of better quality, as experts can understand the questions from this methodology better than the other two methodologies (fixed and quantiles). Additionally, it allows for more consistent, accurate and reliable scenario data that can be used for operational risk capital estimation. It also promotes ownership of the scenario data and thus ownership of the capital estimates that results from the scenario analysis process.

Frachot *et al*. (2003) proposed that a potential loss amount from the experts be elicited with its corresponding probability of occurrence. An average duration (duration) is defined as the average waiting time between two losses exceeding a certain loss amount (x). That is, the business experts have to provide estimate amount x for which it would take d years on average for a loss greater than the x amount to materialise. Hence, in building the subjective loss distribution, the experts will provide a loss amount for each of the given durations. Alderweireld *et al.* (2006) recommended that at least three sets of data consisting of x and d (buckets) must be provided by the experts in order to calculate a meaningful capital amount. This number is directly related to the number of parameters that are being estimated.

Table 2.3: Duration approach

Duration	*1*	*10*	*20*	*50*
Estimated Loss Amount	X_1	X_2	X_3	X_4

Figure 2.2: Duration approach[22]



2.8 Robustness tests

Robustness tests are used to assess the stability of the model. A model is considered to be robust when it is not too specific in its representation of the data sample. Robustness tests are used to avoid having to change the model for each new data sample. Two kinds of test can be performed to assess the robustness, namely bootstrapping and stress testing. Additional context can be found in BCBS (2006), Opdyke (2014) and Chernobai and Rachev (2006).

[22] Source: Frachot *et al*. (2003)

2.8.1 Bootstrap testing

Originally developed by Efron (1979), the essence of bootstrapping is that one can have an understanding of a sample through resampling the data set under investigation, estimating the parameters of each individual sample to assess the variability in the parameters (Frachot *et al.*, 2003). For a given data set, the data is re-sampled randomly a large number of times. Each re-sampled data set is fitted, and the volatility of the derived parameters of the candidate function is computed. The model is considered to be robust if the volatility is under a certain arbitral quantum. As a further test, specific central parameters (average values of the parameters obtained from the several fitted samples) may be adjusted with the volatility, and the VaR recalculated and compared with the VaR calculated with the unadjusted central parameters (the bootstrapped VaR) (Efron and Tibshirani, 1993).

2.8.2 Stress testing

This test assesses the stability of the model to outliers. The model is stressed by adding twice the maximum loss amount to the original sample and refitting the parameters. The VaR is then recalculated, with the latter being called the stressed VaR. If the ratio of the stressed VaR to the original VaR is less than 2, then the model is considered robust (BCBS, 2006).

2.9 VaR calculation using the loss distribution approach

The work by Shevchenko (2010) forms the basis of this section. The calculation of ALD for operational risk quantification typically uses one of the following three methods: Monte-Carlo simulation as suggested in Klugman *et al*. (1998), Panjer's Recursive Algorithm (Panjer, 2006), and Fourier Transformation (BCBS, 2006). In all three methods, smooth theoretical distributions must be fitted to match the loss data, especially for severity, since empirical distributions from limited loss data are unlikely to generate robust figures. Due to certain characteristics of loss data for operational risk quantification, these methods need to be re-evaluated and compared so that informed decisions can be made to determine when and how to use them. Of the three methods, Monte Carlo simulation is the most practical and reliable. In addition, simulation seems to be most flexible and its logic most easily understood and defensible (see Frachot *et al.*, 2003).

2.9.1 Monte Carlo simulation

Whenever a closed form solution is difficult to obtain, simulation is the first option that researchers consider in most instances. This applies to the calculation of the aggregate loss distribution modelled within the actuarial framework that generates the aggregate distribution from two inputs: event frequency and loss severity. The simulation engine simply mimics this logical path by first generating an event frequency number *N*, and then generating individual losses *N* times according to some pre-specified severity distribution. A simulated aggregate loss is obtained by simply summing up the *N* individual losses. This is just one simulated outcome. By iterating this process many times one can obtain a collection of simulated outcomes that may be regarded as a sample representation of the actual aggregate loss distribution from which important statistics such as the mean, median, variance and percentiles can be calculated. It has been shown that 1,000,000 iterations produces reasonably stable results at the 99.9% confidence level (Frachot *et al.*, 2003; Dutta and Perry, 2006). However, the stability of the results will depend not only on the number of iterations, but also on the error surrounding the frequency and severity parameter estimates. Monte Carlo simulation provides a robust, flexible way to perform distribution integration and aggregation to arrive at global loss distributions (Dutta and Perry, 2006). Simulation methods for aggregation were also proposed and used by Mignola and Ugoccioni (2006). De Fontnouvelle *et al*. (2004) and Bocker and Kluppelberg (2005) agree that simulation is seen as a flexible route which can be made to incorporate new logical steps (examples of which are insurance, or diversification) in loss generation that would alter the resultant distribution.

2.10 Regulatory capital

The regulatory capital is defined: the VaR at 99.9% (VaR = EL + UL). Both EL and UL are used in the regulatory capital quantification. For regulatory capital, the 99.9th percentile is always used (BCBS, 2006; ORX, 2010), while other percentiles (confidence intervals) may be used for an economic capital (Basel II Pillar 2) calculation, depending on the target credit rating of the bank (Frachot *et al.*, 2003).

2.11 Chapter summary

The structure and approach to the literature review is premised on Sundmacher (2007)'s case study based analysis. Sundmacher (2007) assesses the case of a financial institution moving from the BIA to the TSA, using hypothesized data and he demonstrates that there might be little incentive for financial institutions to move from BIA to TSA. The underlying thought put forward by Basel II is that as financial institutions move from TSA to AMA, *a priori* lower regulatory capital charge is attained as reward. Francesco and Ardita (2012) test the validity of this underlying thought, and in the process assess the profitability of using AMA through a cost–benefit analysis for Albanian financial institutions. The decision as to which quantification method to opt for is viewed as a cost / benefit trade-off between the developmental costs, the data collection, and collation costs, against the benefits of regulatory capital relief. Kaiser and Kohne (2006) query the AMA assumption that the summation of high percentiles of VaR is an ideal indicator of operational risk within a bank as this means that the worst possible outcomes occur simultaneously. Added to this, should the other AMA assumption of perfect correlation across Operational Risk Cells (ORCs) be assumed valid, then the capital charges of the various ORCs should be summed, and in the process effectively resulting in a higher capital charge than that determined by the simpler approaches. In contrast El Arif, F. Z. and Hinti, S. (2014) state that AMA methods lead to an *a priori* lower capital charge in comparison to BIA, and additionally state that though the gross implementation costs of AMA may be deemed as high, its marginal cost is not. Laycock (2014) takes cognisance of the cons surrounding AMA, but is of the opinion that despite these, AMA models are still preferable to TSA and AMA, especially in relation to risk sensitivity and risk management support.

The complexities in the quantification of operational risk using AMA are highlighted as data shortage, the nature of operational risk, and the lack of a strong risk sensitive exposure measure in operational risk modelling. Additionally, risk data gathered during an economic expansion is deemed to be unsuitable to be used during a recession. Some of the qualitative drawbacks of AMA include being able to do just as much risk management as AMA when using simpler approaches; the fact that only large international banks are permitted to use AMA, thus giving them unfair advantage compared to smaller competitor banks; there being no guarantee of a capital benefit post gradating to AMA, and the exorbitant development costs for the internal models. Notwithstanding the above, some expected benefits of gradating to AMA are highlighted as: elimination of regulatory arbitrage (as the capital charge is entirely based on the individual's bank risk exposure to operational losses); an increased level of flexibility in incorporating innovation in the quantification process (internal models); AMA's consideration of risk controls, diversification benefits, as well as risk transfer contracts (insurance), which effectively reduces the capital charge; that it encourages banks to improve risk management processes and procedures, and a reduced compliance cost owing to alignment between regulatory and economic capital. Francesco and Ardita (2012) conclude, in agreement with Nash (2003), that financial institutions should not take it as a given that changing to AMA will definitely result in a capital benefit, but should rather explore all available quantification methodologies in a bid to identify the ideal method that takes the idiosyncrasies of the particular bank into account.

In summarizing the technical section of this chapter, I do so as follows: Extreme operational risks are risks which occur when unexpected circumstances prevail (largely regarded as tail events), *e.g.* owing to significant failures in the control environment, or abnormal increases in business volumes / values. In the general case, these losses tend to be low frequency and high impact risks (*e.g.* massive frauds or rogue trading). Basel II regulatory guidelines for AMA state that a financial institution is required to ensure that its quantification method for capital captures potentially tail loss events, and that it is comparable to a one year holding period and a 99.9 percentile confidence interval. Measuring the regulatory capital requirement using VaR aligns with this requirement. A bank that intends on adopting AMA, and convincingly meet the supervisory soundness standards is also required to demonstrate the use of the key data elements (ILD, ELD, scenario analysis, and BEICFs) in its risk measurement system. In quantifying operational risk, two variables need to be defined, namely the frequency and the severity of the event, where frequency refers to the number of events that occur within a given time period. Empirical evidence has thus far suggested that operational loss frequency can be modelled using: the Poisson distribution, the negative binomial distribution, or the binomial distribution. With regard to modelling severity, in this thesis particular focus is placed only on the following distributions; the Lognormal, Weibull, Burr, Generalized Pareto, Pareto and Gamma distributions. To fit empirical data to a theoretical distribution the Maximum Likelihood Estimation (MLE) technique is used. The statistical tests discussed in the chapter are the Anderson-Darling, Kolmogorov-Smirnov Test, and Cramer-Von Mises tests. In instances that the GOF test passes all two distributions, an additional screening criterium to support the model selection process can be applied, namely the AIC. Scenario analysis is a way to assess plausible extreme events on the bank's operations, and assign likelihood and severity estimations to the range of possible outcomes. Scenarios are forward-looking and provide coverage mainly for the extreme tail loss events the bank has not yet experienced, but which are likely to negatively impact its solvency. The Duration approach forms the basis for the estimation of the scenario data that is finally used in capital calculation. After severity buckets for each duration have been estimated, two distributions are considered in determining a distribution that would best describe the loss distribution. These points (buckets) are used as inputs to a weighted least-squares approximation to determine the distribution that would best describe the severity estimates. To assess the stability of the model, robustness tests are used, which avoids having to change the model for each new data sample. Two kinds of test can be performed to assess the robustness: Bootstrapping and Stress testing. The chapter concludes by looking at the calculation of aggregate loss distributions for operational risk quantification, typically using one of the following three methods: Monte-Carlo simulation, Panjer's Recursive Algorithm and Fourier Transform. Of the three methods, Monte-Carlo simulation is practical and reliable. In addition, simulation seems to be most flexible and its logic most easily understood and defensible. The resultant regulatory capital is defined as the VaR at 99.9%. The next chapter focuses on the research design, sources of data, and sample population.

CHAPTER 3
DATA AND RESEARCH METHODOLOGY

3.1 Introduction

The chapter explains the methodology employed in this study. This chapter gives an overview of the research design, data collection methods, research population, data sample, data presentation and research analysis employed in this study. Although a comprehensive methodology to the subject matter was developed in chapter two, the research design gives in extensive detail the – nuts and bolts – of executing the proposed approach. Overall, the research design emphasises the calculation process in quantifying the capital requirements using both AMA and TSA, and highlights the AMA benefit as the difference between the two calculated quanta.

3.2 Data collection methods, research population

I test the validity of Basel II's underlying thought as detailed in 2.2 of the preceding chapter, and in the process assess the profitability of using AMA through a cost–benefit analysis for South African financial institutions. In doing so a case study structure on one instance of data has been adopted owing to the fact that historical data is often not available. The net effect is that uniform historical data upon which operational risk capital charges can be built is lacking. In the thesis, I delve into the underlying operational risk profile for the subject matter bank to thoroughly review across its range of business activities in order to identify and estimate the model input requirements, here proposed. Nonetheless a consented effort has been made to shy away from elaborate descriptive stats in a bid to protect the identity of the South African subject matter bank.

3.3 Data Analysis

This section aims to provide a descriptive overview of the data across some of the metrics outlined in Chapter 2. ILD and ELD are among the four data elements that a bank using AMA in managing and measuring operational risk needs to use. ILD portrays a good view of the bank's risk profile, and hence it can be used as a foundation when measuring the risk and ensuring that the outcomes of the risk measurement process are related to the current risks and emerging risks that are pointed out by the ILD. The ILD analysed for this thesis is based on gross loss amounts before any recoveries, and covers a period of 5.5 years, from 2007 to June 2012. The ILD data was sourced from one of South Africa's financial institutions (Data extracted from a SAS depository, onto Excel), with all relevant sanction having been attained. Figure 3.1 details some of the descriptive statistics of the ILD used for this thesis (showing range, number of losses, cumulative loss amount within the range and number of losses within the range): -

Figure 3.1: ILD Loss Ranges[23]

Loss amount range ('000)	No of losses	Loss amount	Ave loss amount
10 - 35	8 896	171 812 168	19 313
35 - 60	1 830	82 324 094	44 986
60 - 155	1 271	115 350 562	90 756
155 - 300	363	77 573 463	213 701
300 - 600	214	90 909 728	424 812
600 - 1000	78	59 319 435	760 506
1000 - 3000	84	140 014 007	1 666 833
3000 - 6000	16	73 787 987	4 611 749
6000 - 12000	12	101 971 091	8 497 591
12000 - 24000	7	120 114 097	17 159 157
24000 - 90000	9	298 801 790	33 200 199
>= 90000	1	97 892 758	97 892 758
Total	**12 781**	**1 429 871 180**	**111 875**

Three event types contribute 94.4% to the total number of losses. These event types are External Fraud (78.2%), Execution, Delivery and Process Management (13.8%), and Clients, Products and Business Practices (2.4%). Moreover, 83% of the loss amounts come from these three event types. However, the major contributor to this amount is the EF (33.4%), followed by EDPM (35%) and CPBP (15%). Of the total losses that were used, 94% of these losses have a value less than R155 000 and 84% of these losses are from Retail. As the loss amount increases, the operational risk profiles of the differing businesses changes. That is, the number of losses in Retail decreases whereas it increases in business units like Business banking, Capital, Corporate and Total finance. This shows that these business units are exposed to risks that are more likely to result in tail events. Survivorship bias within the data set, and its possible impact on the VaR was not explored as it is beyond the scope of this thesis (though discussed in the preceding chapter). Table 3.1 below shows the various business units on the vertical, against the Basel II loss event types. The table shows that most of the infrequent events that have higher impact are mostly in the CPBP event category and some events are in the EDPM category. These events are different from those frequent but low impact events that can be accepted by business as part of their predictable, day to day, stable and expected losses that are deemed as a cost of doing business. Most of these losses fall under CPBP (29%) in Capital (40% of the 29%) and Total finance (40% of the 29%), and also in EDPM (59%) in Total Finance (60% of the 59%) and Capital (20% of the 59%).

[23] Source: ILD of one of the big four banks in South Africa

Table 3.1: ILD[24]

		BDSF	CPBP	DPA	EDPM	EF	EPWS	IF	Total
Business Banking	Count	5	19	-	157	183	11	4	379
	Sum	548 380	34 818 296	-	60 082 289	33 829 207	4 205 839	985 574	134 469 584
	Average	109 676	1 832 542	-	382 690	184 859	382 349	246 393	354 801
	Median	30 966	45 237	-	45 995	30 378	130 136	90 024	38 857
	Max	285 030	28 149 581	-	27 827 821	6 149 236	2 200 825	791 389	28 149 581
	Std Dev	128 367	6 423 326	-	2 312 920	786 808	647 646	365 116	2 146 602
	Vol	1.17042	3.50515	-	6.04385	4.25626	1.69386	1.48184	6.05016
Capital	Count	12	28	-	104	14	21	2	181
	Sum	3 289 899	114 068 883	-	90 914 268	864 051	5 981 665	5 144 086	220 262 852
	Average	274 158	4 073 889	-	874 176	61 718	284 841	2 572 043	1 216 922
	Median	99 797	22 392	-	98 003	20 997	141 599	2 572 043	75 120
	Max	1 363 541	52 004 465	-	29 191 620	593 925	1 642 464	2 909 276	52 004 465
	Std Dev	393 146	12 284 355	-	3 647 823	153 192	405 542	476 919	5 648 291
	Vol	1.43401	3.01539	-	4.17287	2.48213	1.42375	0.18542	4.64146
Corporate	Count	87	13	17	333	471	9	16	946
	Sum	20 299 273	915 490	495 326	84 136 988	62 638 157	1 745 696	1 607 670	171 838 600
	Average	233 325	70 422	29 137	252 664	132 990	193 966	100 479	181 648
	Median	34 988	58 586	23 261	35 241	46 010	73 718	96 420	41 846
	Max	6 339 463	169 657	75 438	22 250 959	24 395 590	836 757	291 854	24 395 590
	Std Dev	805 435	61 788	18 125	1 385 033	1 125 416	270 907	77 976	1 169 441
	Vol	3.45199	0.87739	0.62208	5.48173	8.46243	1.39667	0.77604	6.43797
Retail	Count	142	46	29	814	9 154	75	180	10 440
	Sum	9 413 797	8 875 213	1 777 443	63 397 942	357 595 422	8 699 508	139 683 223	589 442 547
	Average	66 294	192 939	61 291	77 884	39 064	115 993	776 018	56 460
	Median	17 120	31 832	36 909	24 469	21 084	35 182	60 442	21 426
	Max	2 462 982	4 925 422	443 985	4 568 329	7 296 274	1 140 945	97 892 758	97 892 758
	Std Dev	286 782	728 617	83 706	228 108	156 045	190 261	7 293 258	974 938
	Vol	4.32589	3.77641	1.36571	2.92880	3.99456	1.64028	9.39831	17.26776
Wealth	Count	12	157	3	273	30	9	32	516
	Sum	1 690 588	12 988 465	210 549	31 917 783	6 836 897	454 032	17 192 031	71 290 345
	Average	140 882	82 729	70 183	116 915	227 897	50 448	537 251	138 160
	Median	48 782	47 174	14 831	32 638	29 940	25 283	63 432	37 307
	Max	957 527	551 452	183 209	2 570 663	3 284 929	157 907	8 879 899	8 879 899
	Std Dev	265 783	97 567	97 890	290 150	677 332	51 456	1 601 872	490 846
	Vol	1.88656	1.17936	1.39479	2.48172	2.97210	1.01999	2.98161	3.55275
GMCCA	Count	-	-	-	-	3	-	-	3
	Sum	-	-	-	-	40 996	-	-	40 996
	Average	-	-	-	-	13 665	-	-	13 665
	Median	-	-	-	-	13 714	-	-	13 714
	Max	-	-	-	-	14 304	-	-	14 304
	Std Dev	-	-	-	-	664	-	-	664
	Vol	-	-	-	-	0.04860	-	-	0.04860
Group HR	Count	-	-	-	5	4	2	1	12
	Sum	-	-	-	13 834 737	106 955	2 741 672	12 841	16 696 205
	Average	-	-	-	2 766 947	26 739	1 370 836	12 841	1 391 350
	Median	-	-	-	1 146 720	26 410	1 370 836	12 841	254 291
	Max	-	-	-	10 702 942	40 667	1 612 670	12 841	10 702 942
	Std Dev	-	-	-	4 474 059	13 656	342 005	-	2 999 961
	Vol	-	-	-	1.61697	0.51072	0.24949	-	2.15615
Group Risk	Count	-	-	-	3	33	7	1	44
	Sum	-	-	-	56 373	731 082	4 363 258	157 997	5 308 709
	Average	-	-	-	18 791	22 154	623 323	157 997	120 652
	Median	-	-	-	12 947	19 001	382 663	157 997	19 598
	Max	-	-	-	31 426	71 792	2 177 183	157 997	2 177 183
	Std Dev	-	-	-	10 952	11 763	718 488	-	348 533
	Vol	-	-	-	0.58286	0.53098	1.15267	-	2.88874
Group Technology	Count	52	-	2	1	98	3	2	158
	Sum	4 757 371	-	214 085	391 223	3 293 881	162 881	2 933 237	11 752 677
	Average	91 488	-	107 043	391 223	33 611	54 294	1 466 618	74 384
	Median	55 619	-	107 043	391 223	16 603	47 084	1 466 618	25 718
	Max	668 450	-	197 400	391 223	484 760	72 000	2 916 331	2 916 331
	Std Dev	108 702	-	127 784	-	60 609	15 422	2 050 204	243 875
	Vol	1.18816	-	1.19377	-	1.80326	0.28405	1.39791	3.27859
Total Finance	Count	1	2	14	73	6	5	1	102
	Sum	47 766	49 149 467	1 654 216	156 849 726	230 652	798 987	37 852	208 768 667
	Average	47 766	24 574 734	118 158	2 148 626	38 442	159 797	37 852	2 046 752
	Median	47 766	24 574 734	36 611	27 599	11 531	133 410	37 852	34 963
	Max	47 766	32 152 098	542 437	34 751 929	160 977	268 269	37 852	34 751 929
	Std Dev	-	10 716 012	157 542	6 338 560	60 279	94 299	-	6 391 410
	Vol	-	0.43606	1.33331	2.95005	1.56806	0.59011	-	3.12271
Total	Count	311	265	65	1 763	9 996	142	239	12 781
	Sum	40 047 072	220 815 814	4 351 620	501 581 329	466 167 299	29 153 536	167 754 511	1 429 871 180
	Average	128 769	833 267	66 948	284 504	46 635	205 307	701 902	111 875
	Median	29 427	42 171	28 954	30 000	21 391	70 545	64 054	22 582
	Max	6 339 463	52 004 465	542 437	34 751 929	24 395 590	2 200 825	97 892 758	97 892 758
	Std Dev	483 181	4 966 768	98 804	1 882 649	308 846	370 287	6 358 880	1 363 070
	Vol	3.75232	5.96060	1.47584	6.61729	6.62257	1.80358	9.05950	12.18389

[24] Source: ILD of one of the big four banks in South Africa

- **External Loss Data**

In assessing the ILD data, I found that in most cases the type of profile that it depicts relates more to the expected loss (EL) than it does to the unexpected loss (UL). The ILD consists mostly of small losses (in terms of severity) and fewer losses that would be regarded as tail losses. The ELD is used to address some of the gaps that are left by ILD due to its inability to capture tail event risks. In this thesis, ELD is not directly incorporated into the model. It is used as an input to the scenario development process where it is deemed to be relevant and in benchmarking the ILD data. The benchmarking has been done to test alignment between the availed data (of the subject matter bank), and other regional banks that are a members of the consortium. For external data, I have used the Operational Riskdata eXchange Association (see section 2.4.1.2 for additional detail).

The figures below show different views of gross loss amounts and frequencies for the 7 Basel II event types. In constructing the figures below, data from 2004 to October 2011 for the ORX data was analysed. The problem with the ORX data is that, it is more quantitative than qualitative as it does not give a detailed description of reported losses (due to anonymity), which would allow one to scale the losses accordingly. This data has been used to benchmark the operational risk profiles to ensure that all possible risks and other emerging risk, if relevant, are considered. ORX has 10 business lines, which include all the 8 Basel II business lines and corporate items and private banking as additional business lines. In Basel II, private banking is classified under retail banking and I do a similar exercise when analysing the ORX data. It should be noted that their event types are named differently, but they can be mapped directly to the 7 Basel II event types.

It should be noted that the amount is in Euros and has not been adjusted for inflation. Also, in the data presented below, all the credit risk related events and the ones that are flagged as deleted from the database have been removed. A reporting threshold of €20,000 applies to the ORX database.

Table: 3.2 ORX losses by business line and event type[25]

		BDSF	CPBP	DPA	EDPM	EF	EPWS	IF	Total
Corporate Finance	Count	29	493	79	1 001	390	259	30	2 281
	Sum	2 519 633	36 316 839	6 079 668	79 608 010	27 836 774	20 800 020	2 445 240	175 606 184
	Average	86 884	73 665	76 958	79 528	71 376	80 309	81 508	76 986
	Median	90 839	69 357	73 661	77 812	65 515	77 606	79 042	74 418
	Max	144 217	147 389	142 070	147 517	147 143	147 622	144 525	147 622
	Std Dev	34 840	41 799	34 285	37 528	34 745	39 740	37 920	38 291
	Vol	0.40	0.57	0.45	0.47	0.49	0.49	0.47	0.50
Trading and Sales	Count	1 382	1 552	111	19 643	1 006	1 073	188	24 955
	Sum	104 778 413	118 135 715	8 208 693	1 514 340 201	75 991 791	82 515 541	14 651 686	1 918 622 040
	Average	75 817	76 118	73 952	77 093	75 539	76 902	77 935	76 883
	Median	74 125	75 682	71 033	74 923	72 180	75 369	75 050	74 791
	Max	147 515	147 577	144 833	147 669	147 377	147 614	147 396	147 669
	Std Dev	38 468	40 514	37 885	37 040	32 922	38 230	38 287	37 254
	Vol	0.51	0.53	0.51	0.48	0.44	0.50	0.49	0.48
Retail Banking	Count	2 229	18 676	2 023	37 923	66 699	15 729	7 314	150 593
	Sum	169 429 659	1 454 988 871	152 924 804	2 930 004 825	4 917 728 028	1 261 561 130	47 091 249	10 933 728 566
	Average	76 012	77 907	75 593	77 262	73 730	80 206	6 439	72 604
	Median	72 101	75 497	72 647	73 663	68 196	80 059	4 393	69 524
	Max	147 561	147 670	147 528	147 670	147 666	147 668	147 482	147 670
	Std Dev	37 846	35 851	34 364	34 577	32 468	36 427	14 425	36 627
	Vol	0.50	0.46	0.45	0.45	0.44	0.45	2.24	0.50
Commercial Banking	Count	468	4 248	128	9 305	8 264	718	486	23 617
	Sum	35 738 601	329 466 466	10 231 305	730 066 926	637 373 354	56 404 185	37 363 844	1 836 644 681
	Average	76 365	77 558	79 932	78 460	77 126	78 557	76 880	77 768
	Median	72 522	76 744	79 544	77 004	74 335	78 313	74 463	75 735
	Max	146 312	147 670	146 518	147 670	147 591	147 459	147 476	147 670
	Std Dev	38 155	38 680	35 314	37 192	34 459	38 866	39 491	36 651
	Vol	0.50	0.50	0.44	0.47	0.45	0.49	0.51	0.47
Clearing	Count	249	135	11	1 906	840	54	51	3 246
	Sum	20 477 800	9 851 832	827 865	148 018 218	59 115 699	3 717 974	3 888 539	245 897 927
	Average	82 240	72 977	75 260	77 659	70 376	68 851	76 246	75 754
	Median	81 589	64 524	63 625	73 703	65 205	60 407	76 044	71 458
	Max	147 128	147 013	147 176	147 464	147 264	145 089	138 919	147 464
	Std Dev	38 644	38 729	47 103	34 696	29 823	42 111	34 405	34 362
	Vol	0.47	0.53	0.63	0.45	0.42	0.61	0.45	0.45
Agency Services	Count	208	441	35	8 317	655	251	61	9 968
	Sum	16 883 685	33 346 007	2 427 725	656 264 609	50 216 438	20 112 364	4 779 245	784 030 073
	Average	81 172	75 615	69 364	78 906	76 666	80 129	78 348	78 655
	Median	77 287	71 623	58 952	76 489	71 267	77 996	81 912	76 042
	Max	147 135	147 651	143 777	147 658	147 098	147 623	146 625	147 658
	Std Dev	36 058	37 986	39 600	36 103	30 101	39 725	38 379	35 954
	Vol	0.44	0.50	0.57	0.46	0.39	0.50	0.49	0.46
Asset Management	Count	190	1 051	25	4 211	126	270	91	5 964
	Sum	14 229 081	82 130 099	1 617 348	327 861 044	9 579 846	20 288 097	6 936 326	462 641 841
	Average	74 890	78 145	64 694	77 858	76 031	75 141	76 223	77 572
	Median	71 417	77 158	60 303	76 001	68 919	74 964	70 434	75 784
	Max	145 964	147 536	146 635	147 627	146 601	147 171	147 504	147 627
	Std Dev	36 271	37 682	38 043	36 643	37 657	39 008	43 822	37 071
	Vol	0.48	0.48	0.59	0.47	0.50	0.52	0.57	0.48
Retail Brokerage	Count	147	6 294	23	3 716	635	1 245	480	12 540
	Sum	10 591 355	498 159 751	1 572 808	287 989 006	49 266 990	97 861 633	37 704 357	983 145 900
	Average	72 050	79 148	68 383	77 500	77 586	78 604	78 551	78 401
	Median	68 659	80 041	67 159	74 276	75 793	78 943	76 390	77 409
	Max	147 601	147 604	142 105	147 589	147 509	147 660	147 487	147 660
	Std Dev	34 799	39 402	38 618	33 976	34 591	39 256	41 457	37 659
	Vol	0.48	0.50	0.56	0.44	0.45	0.50	0.53	0.48
Corporate Items	Count	169	635	326	1 623	425	2 675	84	5 937
	Sum	13 437 087	51 255 801	26 646 781	125 453 048	33 951 550	213 907 717	6 159 178	470 811 162
	Average	79 509	80 718	81 739	77 297	79 886	79 966	73 324	79 301
	Median	73 708	82 501	83 153	75 682	75 470	81 205	74 192	79 494
	Max	146 990	147 494	147 208	147 593	146 858	147 457	144 244	147 593
	Std Dev	37 950	38 216	37 204	37 816	32 758	39 512	39 634	38 309
	Vol	0.48	0.47	0.46	0.49	0.41	0.49	0.54	0.48
Total	Count	5 071	33 525	2 761	87 645	79 040	22 274	8 785	239 101
	Sum	388 085 314	2 613 651 381	210 536 997	6 799 605 887	5 861 060 470	1 777 168 661	161 019 664	17 811 128 374
	Average	76 530	77 961	76 254	77 581	74 153	79 787	18 329	74 492
	Median	73 207	76 415	73 276	74 797	68 942	79 740	5 193	71 553
	Max	147 601	147 670	147 528	147 670	147 666	147 668	147 504	147 670
	Std Dev	37 887	37 371	35 140	35 746	32 704	37 273	33 819	36 848
	Vol	0.50	0.48	0.46	0.46	0.44	0.47	1.85	0.49

[25] Source: Operational Riskdata eXchange Association (ORX)

ORX shows a profile that is more similar to the ILD profile discussed above. EDPM (38.2% - loss amount and 36.7% frequency) leads the top three event types, followed by EF and CPBP. Unsurprisingly, retail banking contributed 43.3% to the number of losses in the EDPM event category. Similar to ILD data discussed above, retail banking contributed 84.4% to the total number EF losses. This can be attributed to the nature of the business and the vulnerabilities that exist in the card business and other retail products.

- **Inputs into the scenario fitting process**

In analysing LDA, the fact that 84% of the losses are below R155, 000 shows that the internal data has an insufficient quantum of catastrophic losses. The loss experience of the subject matter bank as shown in the composition of the data certainly failed to provide a fully comprehensive sense of the range of potential operational risk loss events experienced / that could be experienced, and hence emphasizing the need for techniques that extend the distribution curve beyond the loss experience of the financial institution in question. In this thesis, this shortcoming was addressed by not only modelling the ILD, but by modelling both the ILD and scenarios (which are based on a hypothetical example). The use of hypothetical data in operational risk quantification is not unusual, a case in point is the Sundmacher (2007) paper. An alternative solution to redressing the lack of tail loss events (low frequency, high severity losses) within an internal data set is the convolution of external data with internal data using mixture models (Extreme Value Theory).

As such, owing to the fact that in this thesis hypothetical data has been used to calibrate the scenario buckets, the frequency and severities of these losses over the next year is unknown (and this is the case in practice). It is thus prudent to do a Monte Carlo simulation when building an aggregate loss distribution (Shevchenko, 2011), as detailed later in this chapter. The building of an aggregated loss distribution using the Monte Carlo simulation method addresses the uncertainty. The Monte Carlo simulation provides a layer of conservatism compared to when the VaR is extracted directly from the parametric distribution (Frachot *et al*., 2003)

For scenarios the severity buckets are fitted using the duration approach (see section 2.7.2 for additional context on the duration approach). Table 3.3 summarises the scenario data that was considered for modelling:

Table 3.3: Scenario data duration buckets[26]

OR Class	Scenario Title	Duration Buckets			
		1 in 1	1 in 10	1 in 20	1 in 50
1	Litigation Claims	500,000	2,000,000	10,000,000	30,000,000
2	Processing Error	1,000,000	5,600,000	7,700,000	10,000,000
3	Fraudulent transfer of funds	2,000,000	5,000,000	10,000,000	18,000,000
4	Fraudulent transfer of funds	200,000	3,000,000	10,000,000	25,000,000
5	Breaching exchange controls	13,950,000	18,600,000	47,000,000	90,000,000
6	Trading errors	973,134	3,600,000	20,000,000	30,000,000
7	Pay away errors	2,200,000	6,000,000	12,000,000	20,000,000
8	Unauthorised Trading	1,000,000	3,378,000	5,000,000	16,454,000
9	Litigation Claims	1,200,000	8,000,000	25,000,000	45,000,000
10	Execution error	1,000,000	2,500,000	20,000,000	40,000,000
11	External Fraud	450,000	2,000,000	20,000,000	35,000,000
12	Internal Fraud	500,000	2,500,000	20,000,000	50,000,000
13	Legal Litigation	500,000	2,400,000	5,100,000	30,000,000
14	Incorrectly charging clients	3,000,000	14,000,000	28,000,000	70,000,000
15	Rogue foreclosure attorney	3 000 000	10,000,000	20,000,000	35,000,000
16	Misappropriation of client funds	575,000	2,100,000	6,200,000	20,000,000
17	Unapproved Products	400,000	5,000,000	7,500,000	10,000,000
18	Execution Errors: Misdeals	200,000	1,100,000	2,000,000	50,00,000
19	Redemptions	123,763	2,379,001	3,463,825	4,020,880
20	Unauthorised movement of funds	1,500,000	5,500,000	8,000,000	12,000,000
21	IT system failure	221,111	1,000,000	4,000,000	20,000,000
22	Damage to building and premises	6,500,00	5,400,000	28,500,000	56,500,000
23	Incorrect employment practices	2,000,000	3,500,000	7,500,000	9,000,000
24	Money laundering regulations	10,000,000	30,000,000	50,000,000	100,000,000
25	Tax-related operational risks	2,500,000	20,000,000	40,000,000	53,000,000
26	Information Security	3,000,000	6,000,000	20,000,000	40,000,000
27	Unavailability of system(s)	1,300,000	10,000,000	14,578,860	32,000,000

3.3.1 The standardised approach (TSA) data

See table 3.4 to see the three year GI numbers used for this thesis, as so extracted from the financial statements of the subject matter bank. The beta for each business line is pre-determined by the BCBS, and its magnitude is said to be largely dependent upon a business line's riskiness (Fatima and Said, 2014).

[26] Source: Hypothetical Example

Table 3.4: Gross operating income and beta factors

	Dec-10	Dec-11	Dec-12	Risk Exposure
Corporate Finance	740 044 332.66	1 525 869 278.45	1 775 550 461.58	1 347 154 690.90
Trading and Sales	10 870 864 744.54	6 751 847 621.24	14 525 727 666.39	10 716 146 677.39
Retail Brokerage	148 936 228.28	168 120 304.65	493 893 766.00	270 316 766.31
Commercial Bank	7 294 870 520.95	7 775 609 760.61	8 760 414 829.46	7 943 631 703.67
Retail Banking	7 731 890 019.81	13 917 532 234.48	7 842 215 813.27	9 830 546 022.52
Payment and Sett	25 389 715.73	75 499 599.29	85 465 748.96	62 118 354.66
Agency Services	311 326 553.35	289 863 006.14	112 968 561.29	238 052 706.93
Asset Management	252 003 636.33	66 427.72	454 776.30	84 174 946.78
Insurance	(1 863 676.81)	150 273.90	-	150 273.90
Total	**27 373 462 074.84**	**30 504 558 506.48**	**33 596 691 623.25**	**30 492 292 143.06**

3.4 Methodologies

This section aims to address the methodology to be applied in this study, as well as review other methodologies applied in previous related studies.

3.4.1 Methodologies used in previous studies

Dutta and Perry (2006) use three different techniques to model the severity distribution in operational risk quantification as follows: Parametric Distribution Fitting (LDA), a method of Extreme Value Theory (EVT), and capital estimation, based on Non-Parametric Empirical Sampling. Dutta and Perry (2006) highlight that in Parametric Distribution Fitting the underlying assumption is that the data is assumed to follow some specific parametric model. In determining this parametric model, the respective parameters are estimated in such a way that the model fits the underlying distribution of the data in some ideal manner. EVT is considered a discipline that largely deals with large operational losses. The final technique is Empirical Sampling / Historical simulation, which is largely drawing at random from an actual data set. Dutta and Perry (2006) provide further an indication of relative popularity among the three options within the financial institutions they studied[27]. Moscadelli (2004) found that EVT appeared to be a popular tool used in better understanding large operational risk losses (additionally referred to in the penultimate chapter of this thesis as areas of further study), largely due to its attention to the tail. However, EVT is not to be seen as the perfect solution as there are specific conditions which are required for its ideal application, and moreover there are far-reaching criticisms of EVT which is fully detailed in literature (see for example, Embrechts *et al.*, 1997; Diebold, Schuermann and Stroughair, 1998; and Embrechts, Lindskog and McNeil, 2003).

[27] For a comprehensive source on the application of EVT to finance and insurance, see Embrechts, Kluppelberg & Mikosch (1997) and Reiss & Thomas (2001)

Shevchenko and Wuthrich (2006) extensively applied the Bayesian Inference Technique within the context of operational risk, which is an alternate to the methods discussed by Dutta and Perry (2006), and Moscadelli (2004). The key fundamentals relating to Bayesian inference is that it is a statistical technique used in fusing expert opinions into data analysis. Berger (1985) gives a good overview of Bayesian inference method whilst Bühlmann and Gisler (2005) do an equally exceptional job on credibility theory (a closely related subject). Shevchenko and Wuthrich (2006) detail how Bayesian Inferences essentially allow for structural modelling, where expert opinions are incorporated into the analysis via specifying distributions (prior distributions) for model parameters. These are updated with new data as it becomes available. At any point in time, the expert may reassess the prior distributions, given the availability of new information (for example, when new policy control is introduced), that will incorporate this information into a model. Shevchenko and Wuthrich (2006) report that Bayesian Inference is hardly used in practice, though they do note that Cruz (2002) mentions it in passing.

3.4.2 Methodologies used in this study

The choice of using LDA in this thesis is premised on the understanding that LDA is one of the most commonly used actuarial modelling techniques. Various quantitative and qualitative aspects of LDA modelling are discussed by King (2001), Cruz (2002), Panjer (2006) and Shevchenko and Wuthrich (2006). The LDA was essentially developed to make better use of loss data when modelling cumulative loss exposure, by initially recognising that the aggregate loss distribution consists of individual events. This distribution can therefore be described in terms of the frequency of events and the respective loss severity (Opdyke, 2014). Dutta and Perry (2006) provide a mathematical illustration by denoting the number (or "frequency") of losses occurring over a specified time period [0, t] with *N (t)*, and the individual loss (or "severity") amounts by $x_1 x_2 x_{3\ldots}$ The random variable describing the Aggregate Loss statistic is then determined as follows:

$$A_{gg}L = \sum x_i \qquad (3.1)$$

Lavaud and Leherisse (2014) mention the assumptions which conform to the AggL statistic, namely that the individual severity random variables are independent of each other and identically distributed (i.i.d), and that they are also independent of the frequency random variable. See also Afambo (2005). Lavaud and Leherisse (2014) further highlight that for most choices of severity and frequency distribution, this distribution cannot be calculated, or is deemed in general difficult to describe, in particular in closed form. Numerical methods to overcome this challenge include Monte Carlo simulation, Panjer Recursion and fast Fourier Transform methods. These are generally used to calculate the aggregate distribution and its relevant statistics, such as the mean and the quantiles. For additional insights see also Klugman, Panjer and Willmot (1998), which gives a sterling overview of the mentioned three techniques. In practice they find that annual loss distribution is typically found using Monte Carlo simulations as opposed to the other two (Panjer and the Fourier). Ultimately the regulatory capital charge when using the LDA is attained by taking the empirical quantile at level $\alpha = 99{:}9\%$ of the compound distribution, which aligns to risk that occurs every thousand years (Frachot, Moudoulaud and Roncalli, 2003; BCBS, 2006).

3.5 Research design

The proposed quantification methodology is grounded in the tenants of various published modelling techniques and portions of existing methodologies. However, the overarching methodology is deemed to be uniquely suited for the South African financial market. BCBS (2006) specifies that the ILD element is the most relevant in the bank's operational risk measurement system as it is directly related to the bank's current activities, hence taking preference ahead of all other proxies. As an AMA candidate bank, the bank is expected to collect loss data under a specified methodology, process and guideline framework. The methodology described in this chapter focuses on the use of the data that is already collected and saved in a loss depository system, in order to calculate the capitalisation amount. The following sections describe the modelling process followed for the quantification of regulatory capital charge for operational risk under AMA using a LDA approach, as well as the TSA calculations.

3.6.1 AMA modelling process design

This section opens up with an outline of the AMA modelling process that was followed in conducting this research:

- **Step A - construction of risk classes**

According to BCBS (2006), operational risk is measured against loss event types, namely: clients, products and business practices (CPBP); business disruption and systems failures (BDSF); employment practices and workplace safety (EPWS); execution, delivery and process management (EDPM); internal fraud (IF); external fraud (EF); and damage to physical assets (DPA). The seven loss-event types are also classified in line with the business lines which, in the case of the subject matter institution for this thesis, are Business Banking, Capital Management, Corporate Banking, Retail Banking and Wealth Management. A blend of business line and loss event type then describes a loss class (Ergashev, 2008) - for example internal fraud in capital management becomes an Operational Risk Class (ORC).

- **Step B – loss data analysis**

The data series was analysed to determine if any of the statistical distributions commonly accepted by the industry to describe extreme events would fit the data. The statistical tests to ensure that the data was stable, robust and sufficient to be used for modelling were conducted and scenario data was fitted in Step C. In cases where the ILD did not pass the statistical tests, only the scenario was used to estimate the capital requirements. All instances where the ILD did not pass statistical tests, I would proceed to step C, however if the ILD passed I would proceed as below.

In essence the following distributions were considered in modelling the loss severities; the Lognormal, Weibull, Burr, Generalized Pareto, Pareto and Gamma distributions. Whilst for operational loss frequency the three distributions considered were the Poisson distribution, the negative binomial distribution and the binomial distribution (De Fontnouvelle *et al.*, 2004). The standard GOF tests were done as described in section 2.6.2. When more than one distribution was considered acceptable, two distributions that best described the data were accepted. This was done through employing the KS and AIC tests (relative tests) (Moscadelli, 2004; Dutta and Perry, 2006). For the best fitting distribution, stress testing and bootstrap testing were conducted to test for robustness and stability of the model (as detailed in sections previous chapter).

- **Step C – scenario analysis:**

Scenario analysis is a way to consider the impact of extreme, but nonetheless plausible, events on the operations, and assign likelihood and severity estimations to the range of possible outcomes. Scenarios are forward-looking and provide coverage mainly for the extreme tail loss events the bank has not yet experienced, but likely to negatively impact its solvency. The Duration Approach formed the basis for the estimation of the scenario data that was finally used in capital calculation (see full details on the scenario analysis in section 2.7). With the average annual frequency at one, during the Monte Carlo simulation simulated, say, one million years, approximately 37% of the years simulated were anticipated not to have losses. This is expected as the scenarios are focusing on rare losses that have a major impact on the bank. The fact that they are rare does not mean that they cannot happen; in some years I have more than five of those events considered to be rare. Thus once the severity buckets for each duration or percentile had been estimated distributions were considered in terms of best describing the loss distribution. These points (buckets) were used as inputs to a weighted least-squares approximation to determine the distribution that would best describe the severity estimates.

- **Step D – Monte Carlo simulation to calculate VaR**

The next step was to calculate the expected loss and the regulatory capital at the 99.9^{th} percentile by means of Monte Carlo simulation. This was done by implementing the accepted statistical distribution, the parameters of the distribution and the estimate of the frequency of an event to occur. Losses for at least 1,000,000 possibilities were simulated and the EL and VaR were calculated as follows:

i) For each simulated year, a random draw from the Poisson distribution was generated by means of statistical and numerical techniques (given the estimated frequency) to determine the number of events that will happen in this year;

ii) For each event in the simulated year, a random loss was generated from the selected statistical distribution by means of statistical and numerical techniques (given the estimated parameters of the distribution);

iii) The sum of these losses was then taken as the aggregate loss for the simulated year;

iv) After losses were simulated for all the years, the expected loss was then defined as the average loss, and the regulatory capital is taken as the 99.9^{th} percentile of these losses simulated for, say, 1,000,000 possibilities, and this is then the Capital requirement for AMA.

Figure 3.1: Modelling process flow

Step A
Construction of Risk Classes
Cluster Event Type combinations are selected to form Operational Risk Classes.

Operational Risk Classes are mapped to Operational Risk Cells

Step B
Internal Loss data Preparation

Calculate modelling frequency (Poisson) and Severity

Fit modelling distributions to each class data

Obtain p value of the KS test and Akaike Information Criterion and select best modelling distribution

Perform robustness and stability tests on class data

Select appropriate ILD distribution parameters

Step C
Scenario data Preparation
Obtain severity buckets for scenario modelling.

Fit scenario distributions to severity buckets and obtain distribution parameters and weighted least squares (wLSA) average.

Select the most suitable risk measurement distribution based on the wLSA value.

Select appropriate scenario distribution parameters.

Step D
Monte Carlo Simulation to Calculate VaR
Simulate the number of loss for the period, randomly drawing from the Poisson distribution.

Simulate individual loss amounts from the selected severity distribution. The number of losses is that obtained for the Poisson distribution above.

Add simulated losses together to obtain the total (aggregate) loss amount for the period.

Repeat 1,000,000 times to obtain an aggregate loss distribution.

Perform the above 4 steps for the scenario, and ILD profiles depending on the final modelling inputs that have been chosen above.

If there is more than one profile, aggregate loss distributions assuming independence of each simulated total loss amount.

3.7 TSA process design

For the TSA the internal business lines (BL) were mapped to regulatory or Basel II specified business lines. Basel predetermined beta factors are multiplied by the GI of each BL to attain the regulatory Operational Risk charge for that business line to arrive at the capital charge for that business line. The resulting amount is the capital charge for that business line. The business lines and their respective beta factors are Corporate finance (18%), Trading and Sales (18%), Retail Banking (12%), Commercial Banking (15%), Payment and settlement (18%), Agency services (15%), Asset Management (12%), and Retail Brokerage (12%). The total capital charge was attained by summing the underlying business lines' capital requirements.

3.8 Chapter summary

This chapter thus highlighted the research design, data collection methods, research population, data sample, data presentation and research analysis employed in this study. For the purposes of the research bank annual reports and publications in local media, trade journals, and operational risk journals were used. Lastly, the internet proved to be a major source of secondary information, through various websites the researcher managed to secure varied articles on the subject matter.

At a high level the research design looked at: the Poisson distribution was used to model loss frequency because of its analytical properties which include the mean being equal to the variance and that the sum of two independent Poisson distributions is also Poisson. In a case where the ILD for an ORC is suitable for modelling, the parameter estimation was performed using the Method of Maximum Likelihood Estimator (MLE). Based on these parameters (A, B and C), the following diagnostic tests are performed in order to conclude as to which distribution best fit: Akaike Information Criterion (AIC) to determine the most suitable distribution for data set; Kolmogorov-Smirnov test at 5% to validate the goodness of fit. Further tests were conducted on the selected distribution to ensure the robustness of the ILD. The following tests are performed: Stress testing to test whether the distribution parameters account for possible tail events. The ratio of stressed VaR to VaR should be less or equal to two for a distribution to be considered for modelling; and Bootstrapping to test the stability of the distribution parameters. For parameters to be considered as stable, their volatility must be less than 25%. The final decision whether or not to include ILD as a simulation input to capital estimation is based on the success or failure of all the above steps. For each of the inputs, whether scenarios or ILD, the aggregated loss distribution was constructed using the Monte Carlo method. In performing the Monte Carlo simulation, 1 million years, each with random severities based on the best fitted distribution materialising and aggregated according to the random frequencies informed by the annual loss average, are simulated. This means that each input (whether scenario or ILD) has its own aggregated loss distribution, but that distribution might be for high severity and low impact losses which do not materialise every year in the case of scenarios. To incorporate the day to day losses, the aggregated loss distribution from the ILD is added to the scenario aggregated loss distribution without sorting both distributions as the assumption is that these losses are independent and random. This allows the aggregation of two or more independent risk profiles within a class or an operational risk cell. For example, adding a simulated first year one of the day to day losses to simulated first year of the high severity low frequency type losses. This gives us a complete picture which accommodates the profiles depicted by the business experience (in terms of actual losses) and the forward looking view (in terms of scenario analysis), and from this an EL and VaR can be extracted.

The instruments employed in the study were analyzed, and the methods of presentation were described. The Operational Risk platform for this thesis is based on SAS Enterprise Governance and Risk Compliance (eGRC). This system offered dashboard and analytical capabilities ideal for this research. The model was operated using the Matlab software application and also required Microsoft Excel to process modelling inputs and outputs. Compiled Matlab® code (executable application) was used for all calculations for modelling operational risk data to estimate a risk-sensitive capital requirement. Matlab® is a sophisticated statistical analysis and modelling software package with various toolboxes containing pre-programmed statistical and mathematical functions. Toolboxes used for calculations in this study include the statistical and optimisation toolboxes. Matlab® is widely used in numerous industries with many diverse applications, including the financial industry, engineering and the military[28]. Chapter 4 analyses and presents data collected with the aid of tables and shows the extent to which research objectives were achieved.

[28] http://inside.mines.edu/~whereman/papers/Hereman-PhysicsWorld-8-April1995.pdf

CHAPTER 4
RESULTS AND ANALYSIS

4.1 Introduction

The prior chapter outlined the steps taken in developing the proposed design and implementation schematics of an Operational Risk Quantification Method for Regulatory Capital using the Basel II's AMA, and the Standardised Approach (TSA). This chapter documents, analyses and discusses the results of the research in line with the objectives of the study stated.

4.2 Internal loss data analysis

In assessing the financial institution's data, it was found that in most cases the type of historical loss profile that it depicted related more to the expected loss portion than unexpected loss. The ILD consisted of mostly small losses (in terms of severity) and fewer losses that would be regarded as tail losses (large in severity, but infrequent). The descriptive statistics of the subject matter bank's loss profile was similar to those of findings of the quantitative impact studies that were conducted by BCBS focusing on operational loss data collection exercises (LDCE). The first two such exercises that are done by the Risk Management Group (RMG) of the BCBS on an international basis was the 2001 LDCE and 2002 LDCE[29]. The study analyzed data from eighty-nine banks that submitted their data. The overarching finding, which is in line with the findings of this study regarding the ILD, was that the loss experience of the subject matter bank certainly failed to provide a fully comprehensive sense of the range of potential operational risk loss events experienced, and hence emphasizing the need for techniques that extend the distribution curve beyond the loss experience of the financial institution in question (case in point is scenario analysis, see RMG's 2001 and 2002 LDCE reports for the full detail on the general loss profile). For the purposes of this research the ELD was used to address some of the gaps that are left by ILD due to its inability to capture tail event risks. The ELD was, however not directly incorporated into the model, though some techniques like the Extreme Value Theory, (EVT) maybe used to combine ILD, and ELD as direct inputs to model, commonly referred to mixture models (Dutta and Perry, 2006).

[29] www.bis.org/publ/bcbs160.htm.

4.3 Summary of scenario data fitting

The inputs to the scenario fitting process are the severity buckets. For scenarios the severity buckets are fitted using the duration approach (see section 2.7.2 for additional context on the duration approach). Table 3.3 summarises the scenario data that was considered for modelling. A total of 27 operational risk cells (ORC) were identified which represent actual and potential loss systems where losses can occur. In all of the scenarios, lognormal was found to be the best fitting distributions based on the fitting criterion, with λ=1. Notwithstanding that in this thesis l assumed a Poisson parameter of one, additional extensive analysis on the effect of this assumption should be carried out (future research). Thus, I do concede that neither sensitivity nor "validation" analyses has been done confirming that this assumption makes it consistent with the historical profile of the given data set.

Nonetheless, the overall distribution with the least wLSA after fitting the scenarios was the lognormal distribution. The Lognormal is a sub-exponential distribution that seemingly adequately estimated the tail properties of this data set. To support and confirm the choice made using the wLSA, different graphical goodness–of–fit tests could be considered, despite them not having been considered in this thesis. These include the box plots for all the parameters and the wLSA, the aggregated loss distribution profile. However, the selection of just the Lognormal from the 4 [Lognormal, Weibull, Burr, Generalized Pareto, Pareto and Gamma distributions] considered distributions needs to be investigated further, with possibly broadening the portfolio of distributions to reflect both heavy and fat tailed phenomena. The additional distributions that can be considered are the Nonparametric–Gaussian, and the Exponential severity distributions (see other possibilities from Synman, 2011).

During the penultimate stage of Monte Carlo simulation, both the frequency distribution and the severity distribution were convoluted to form a single aggregate loss distribution which is then used to determine the VaR. The largest operational risk cell or class is class number 22, with a VaR of R353 million (see Table 4.1).

Table 4.1: Scenario data capital output (scenario parameters, VaR)

OR Class	Distribution	A	B	Freq.	wLSA[30]	VaR
1	Lognormal	14.06168	1.5548	1	0.86	160 272 259
2	Lognormal	14.79961	0.758	1	0.07	34 375 892
3	Lognormal	15.02056	0.8549	1	0.76	54 753 701
4	Lognormal	13.4109	1.7842	1	0.37	168 543 997
5	Lognormal	16.93749	0.7151	1	1.18	262 084 752
6	Lognormal	14.93534	1.202	1	0.65	132 989 110
7	Lognormal	15.13993	0.8513	1	0.63	60 576 321
8	Lognormal	14.43572	1.0959	1	1.07	59 812 455
9	Lognormal	14.98556	1.332	1	0.42	205 742 853
10	Lognormal	14.87185	1.334	1	0.78	187 649 676
11	Lognormal	14.45428	1.5127	1	0.67	209 854 237
12	Lognormal	14.31579	1.6948	1	0.71	314 960 845
13	Lognormal	14.0314	1.5804	1	1.15	168 419 703
14	Lognormal	15.59286	1.2213	1	0.7	274 848 716
15	Lognormal	15.50284	0.9436	1	0.57	112 184 264
16	Lognormal	14.04517	1.3702	1	0.98	90 735 328
17	Lognormal	14.47808	0.9604	1	0.05	42 249 872
18	Lognormal	12.90182	1.244	1	0.61	19 804 547
19	Lognormal	13.93846	0.9083	1	0.12	21 409 434
20	Lognormal	14.79807	0.7784	1	0.26	35 920 830
21	Lognormal	13.30229	1.7286	1	1.07	126 385 922
22	Lognormal	14.63594	1.6202	1	0.5	352 652 933
23	Lognormal	15.0356	0.5543	1	0.69	28 036 795
24	Lognormal	16.62515	0.9028	1	0.74	309 223 767
25	Lognormal	15.79127	1.0569	1	0.21	205 253 629
26	Lognormal	15.55257	0.985	1	0.93	132 739 752
27	Lognormal	14.87235	1.1973	1	0.33	124 266 394

4.4 Summary of internal loss data fitting

Of the total of 27 classes, only 16 classes had more than 25 data points. Of the 16 classes that had more than 25 data points, only 5 classes passed all the robustness tests to allow the data to be directly used in the model as an input. In Table 4.2, most of the datasets that failed the bootstrapping had heavy tails. For example, ORC 14 encompasses two profiles in one data set. That is, even though they have a few losses that result to heavy tails in their context, their data is dominated by small losses. Hence, during the process of resampling, especially in the scale parameter, the volatility becomes very large. For stress testing, classes that have ILD dominated by the low severity losses with a single outlier (based on the data set) have less sensitive parameters. In instances where the ILD captures two different profiles in one data set, where it is dominated by low severity events but there are some high severity events as well,

[30] Weighted Least Squares Approximation

this results in some instabilities during the fitting process, as the MLE better fits the body than the tail of the distribution. Hence, the stressed VaR exceeds the ratio of 2 when compared to the VaR. For ORC's where no distribution exists, the data was insufficient for modelling. This was the case for OR class 1, 4, 7, 8, 9, 12, 19, 24, 25, 26 and 27.

Table 4.2: Internal loss data capital estimates (ILD parameters, VaR)

Class Cell	Distribution	A	B	C	Freq	Stress testing	Bootstrapping	Decision	VaR
1	-	-	-	-	-	-	-	-	-
2	Lognormal	9.4952	2.1484	-	26.17	Reject	Accept	Reject	94 958 000
3	Lognormal	3.0297	3.39	-	30.5	Reject	Reject	Reject	195 900 000
4	-	-	-	-	-	-	-	-	-
5	Burr	0.0052	9991.08	80.55	4.67	Reject	Reject	Reject	83 241 000
6	Lognormal	10.6409	2.2434	-	17.33	Reject	Accept	Reject	297 120 000
7	-	-	-	-	-	-	-	-	-
8	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-
10	Lognormal	2.7983	3.5783	-	35	Accept	Reject	Reject	398 390 000
11	Lognormal	10.2102	1.3581	-	72	Accept	Accept	**Accept**	15 802 000
12	-	-	-	-	-	-	-	-	-
13	Lognormal	8.0061	2.4166	-	7.67	Reject	Reject	Reject	42 228 000
14	Lognormal	5.6802	2.5916	-	135	Accept	Reject	Reject	94 960 000
15	Lognormal	9.2877	1.1066	-	1525	Accept	Accept	**Accept**	57 157 000
16	Lognormal	10.16	2.1782	-	30	Reject	Accept	Reject	200 220 000
17	Lognormal	10.4041	1.2864	-	21.33	Accept	Accept	**Accept**	7 575 900
18	Lognormal	8.6805	1.8004	-	30.83	Accept	Accept	**Accept**	14 066 000
19	-	-	-	-	-	-	-	-	-
20	Lognormal	9.0614	2.8436	-	5.33	Reject	Reject	Reject	366 630 000
21	Burr	0.003	256.2487	68.41	43	Accept	Reject	Reject	4 996
22	Lognormal	9.6027	1.2824	-	8.17	Reject	Reject	Reject	2 416 300
23	Lognormal	10.4427	1.7157	-	20.83	Accept	Accept	**Accept**	35 752 000
24	-	-	-	-	-	-	-	-	-
25	-	-	-	-	-	-	-	-	-
26	-	-	-	-	-	-	-	-	-
27	-	-	-	-	-	-	-	-	-

Of the 16 classes that had sufficient data points, only 5 classes passed all the robustness tests to allow the data to be directly used as an input into the model. The BCBS 196 (par 165), states that there should be an optimum balance between the granularity of the class, and the volume of historical loss data for the respective ORCs especially when used in conjunction with a LDA. Although the definition and number of ORCs fall within the range of AMA practice, the mapping of internal losses into 27 cells results in some ORCs having very few observations, often insufficient data for modelling (according to the criterion chosen to allow modelling of ILD). The insufficient number of data points contributes to limit the role of ILD over final capital figure. A coarser ORCs scheme could be evaluated and tested in order to be aware of the impact of the granularity structure used in this thesis on the capital.

4.5 Summary of stand-alone regulatory capital using AMA

This final step was to calculate the regulatory capital at the 99.9th percentile by means of Monte Carlo simulation. This was done by implementing the accepted statistical distribution, the parameters of the distribution and the estimate of the frequency of an event to occur. Losses for at least 1,000,000 possibilities were simulated and VaR were calculated as detailed in Step D in chapter 3. Assessing the use of 1 million data points fulfils the minimum requirements of 1,082 observations for a typical Poisson distribution, and 1 million points for a severity distribution like lognormal. In section 1.2.1(d) of this thesis, the BCBS stipulates that regulatory capital must be composed of expected loss (EL) and unexpected loss (UL), unless permission has been granted by the relevant regulators to implement additional capital discounts. The following table details the overall outcome of this thesis, showing the individual EL and Var for each ORC:

Table 4.3: Stand-alone regulatory capital using AMA

Cell	EL	VaR
Cell1	4 253 538	158 984 224
Cell2	7 007 372	41 547 632
Cell3	7 148 871	56 972 316
Cell4	3 265 174	168 435 200
Cell5	29 343 740	261 588 336
Cell6	15 330 386	166 387 872
Cell7	3 390 424	60 020 020
Cell8	7 817 782	205 501 856
Cell9	8 317 454	187 215 152
Cell10	12 194 215	214 488 832
Cell11	6 918 291	318 781 920
Cell12	4 317 652	169 687 824
Cell13	12 450 980	271 859 200
Cell14	57 647 432	162 065 680
Cell15	19 365 968	172 976 832
Cell16	3 077 603	42 249 720
Cell17	7 486 977	52 324 000
Cell18	1 705 683	21 330 804
Cell19	3 611 945	35 859 360
Cell20	6 186 179	151 924 928
Cell21	8 390 612	347 731 328
Cell22	8 005 730	41 949 584
Cell23	24 961 614	308 966 528
Cell24	12 586 047	205 077 104
Cell25	9 222 884	133 354 136
Cell26	5 879 475	123 923 936
Total	**289 884 000**	**4 081 204 324**

Thus from the 1.2.1 (d) stipulation, VaR = EL + UL, in this instance the overall VaR is R4 billion, and the EL is R289.88 million, therefore the UL is given by **VaR – EL = R4 081 204 324 - R289 884 000, will give the Unexpected portion of R3, 791, 320, 324.** However, it is conceded that according to BCBS 196 the arithmetic mean has been known to cause an inaccurate view of the expected loss quantum due to its sensitivity to tail losses. The BCBS text goes on to advocate for the use of statistical approaches that do not seem to exhibit the same flaws as the arithmetic mean, namely the median, trimmed mean. In the thesis, the chosen EL measure is the expectation of the annual loss distribution, *i.e.* the arithmetic mean of the annual losses. The impact of this could also be an element of further study.

4.6 Summary of regulatory capital using TSA.

For the TSA the internal business lines were mapped to a series of regulatory (Basel II) business lines. Basel predetermined beta factors are multiplied by the GI of each BL to attain the regulatory Operational Operational Risk charge for that business line (BSCS, 2006) to arrive at the capital charge for that business line. The resulting amount is the capital charge for that business line. The business lines and their respective beta factors are Corporate Finance (18%), Trading and Sales (18%), Retail Banking (12%), Commercial Banking (15%), Payment and Settlement (18%), Agency Services (15%), Asset Management (12%), and Retail Brokerage (12%). The total capital charge was attained by summing of the underlying business lines' capital requirements.

Table 4.4: Stand-alone regulatory capital using TSA

	Dec-10	Dec-11	Dec-12	Risk Exposure	Beta Factor	Capital Requirements
Corporate Finance	740 044 332.66	1 525 869 278.45	1 775 550 461.58	1 347 154 690.90	18%	242 487 844.36
Trading and Sales	10 870 864 744.54	6 751 847 621.24	14 525 727 666.39	10 716 146 677.39	18%	1 928 906 401.93
Retail Brokerage	148 936 228.28	168 120 304.65	493 893 766.00	270 316 766.31	12%	32 438 011.96
Commercial Bank	7 294 870 520.95	7 775 609 760.61	8 760 414 829.46	7 943 631 703.67	15%	1 191 544 755.55
Retail Banking	7 731 890 019.81	13 917 532 234.48	7 842 215 813.27	9 830 546 022.52	12%	1 179 665 522.70
Payment & Sett	25 389 715.73	75 499 599.29	85 465 748.96	62 118 354.66	18%	11 181 303.84
Agency Services	311 326 553.35	289 863 006.14	112 968 561.29	238 052 706.93	15%	35 707 906.04
Asset Management	252 003 636.33	66 427.72	454 776.30	84 174 946.78	12%	10 100 993.61
Insurance	(1 863 676.81)	150 273.90	-	150 273.90		-
Total	**27 373 462 074.84**	**30 504 558 506.48**	**33 596 691 623.25**	**30 492 292 143.06**	**-**	**4 632 032 739.99**

Table 4.5 summarises the AMA and TSA regulatory capital calculation: -

Table 4.5: Consolidated regulatory capital for TSA and AMA

	Aggregate TSA	Aggregate AMA
Group Consolidated	**4 632 032 739.99**	**4 081 204 324**

Financial institutions in South Africa are given the option to use the following operational risk capital estimation methods which are listed in their descending order of risk sensitivity: the AMA, the TSA or the BIA. The BIA and TSA are predetermined by the SARB, whilst AMA relies on internally generated methodologies. These estimation approaches were initially introduced by the BCBS, largely premised on an increasingly sophisticated approach to the quantification of capital to incentivise financial institutions to improve their risk management and measurement methods, while benefiting from a lower capital charge through gradating from the least to the most sophisticated measurement tool. Financial institutions have to make a substantial investment in order to move from TSA to AMA. However the benefit for moving to AMA is not readily obvious. This study extended Sundmacher (2007)'s work, and tested one instance of AMA regulatory capital against that of TSA, in a bid to crystalise the rand benefit that South African financial institutions stand to attain (if at all) should they move from TSA to AMA. It must be noted however that the goal of the thesis was *not* to explicitly measure the costs of the switch but to determine whether the benefits are such that they would warrant a bank then assessing the costs of switching. The rand benefit for this instance of the data analysed (2007 to 2012), is found to be TSA – AMA (**4 632 032 739.99 - 4 081 204 324 = R550, 828, 415**). In case of moving from the TSA to the AMA, there is a substantial incentive for financial institutions in South Africa to do so. AMA being risk sensitive awards the subject matter bank a capital benefit of **12%** in comparison to its TSA calculated capital (which is largely based on a beta factor arbitrarily applied against the gross operating income of that segment of the business).

Using this illustrated process banks can calculate the rand benefit for multiple years. Given multiple year benefit one may determine the threshold of initial investment for the bank. This initial benefit would be for changes in IT systems in order to effect the change from TSA to AMA. On the basis that in adopting AMA, a significant number of international banks adopt LDA[31]. In conducting this thesis, emphasis was placed on all key building blocks of an LDA in a bid to show a sound mathematical framework for the South African market, and demonstrate the level of rigor required within the LDA approach.

[31] www.bis.org/publ/bcbs160.htm.

4.7 Chapter summary

The chapter presented the research findings and went on to analyze them. For each of the inputs, whether scenario, ILD, ELD an aggregated loss distribution was constructed using the Monte Carlo method. In performing a Monte Carlo simulation, 1 million years, each with random severities based on the best fitted distribution that materialized and was aggregated according to the random frequencies informed by the annual loss average, were simulated. This meant that each input had its own aggregated loss distribution. In all of the scenarios, lognormal was found to be the best fitting distribution based on the fitting criterion stated in the prior chapter (see also Moscadell, 2004). From the total of 27 classes, only 16 classes had more than 25 data points. From the 16 classes that had more than 25 data points, only 5 classes passed all the robustness tests to allow the data to be directly used as an input into the model. Most of the datasets that failed the bootstrapping had heavy tails. The following chapter presents the summary and conclusions as well as the recommendations, and suggestions for further research.

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the entire research, and goes on to give recommendations on the area of study, a conclusion of the research study and suggestions for future research. The conclusions will reflect on how the objectives to the study highlighted in the first chapter have been achieved.

Operational risk has increased in importance in recent years due to massive operational losses that headlined financial markets across the world. The structure and approach to this study employed a case study based analysis found in Sundmacher (2007) who assessed the case of a financial institution moving from the BIA to the TSA, using hypothesized data. In any event ILD is regarded as proprietary information, and as such in this thesis I limit the scope of my work to one set of collated data that belongs to one of the big four banks domiciled in South Africa. Notwithstanding that the data set is restricted to just one of the big four, the scope of this thesis is to illustrate a methodology that is representable (or generalisable) to the other big banks within South Africa. Effectively, this study extends the work of Sundmacher (2007) by taking cognizance of the fact that financial institutions have to make a substantial investment in order to move from TSA to AMA, and thus the benefit for moving to AMA is not readily obvious. To quantify the capital benefit, the TSA and an AMA developed model is applied to one instance of live data. It must be noted however that the goal of the thesis is *not* to explicitly measure the costs of the switch but to determine whether the benefits are such that they would warrant a bank then assessing the costs of switching.

For the TSA, Basel predetermined beta factors are multiplied by the GI of each BL to attain the regulatory Operational Risk charge for that business line. The capital charge for each business line was summed up to obtain the total operational risk capital charge under the TSA. The AMA modelling process was done in four stages. Firstly, risk classes were constructed based on the business line of the analysed bank. Secondly, the frequency of loss was modelled using the Poisson distribution. Additionally, loss distributions were considered in terms of their modelling ability of the loss data. Distributions which include Lognormal, Weibull, and Burr, Generalised Pareto, Pareto and Gamma distributions were used in modelling loss severities. The KS and AIC tests were employed to gauge the goodness of fit of the mentioned loss distributions, and hence making a choice of the two distributions to be used at a further data analysis stage. Thirdly, scenario analysis was conducted to measure the impact of the risk events. This was based on the two chosen distributions, namely the Lognormal and Burr distributions. Finally, the Monte Carlo technique was used to simulate at least 1,000,000 scenarios with an overall aim of calculating the expected loss and VaR. The operational risk capital charge using AMA was taken as the 99.9th percentile of the losses simulated.

It is found that there is a substantial incentive for financial institutions in South Africa to do so. AMA being risk sensitive awards the subject matter bank a capital benefit of **12%** in comparison to its TSA calculated capital (which is largely based on a beta factor arbitrarily applied against the gross operating income of that segment of the business). Using this illustrated process banks can calculate the rand benefit for multiple years. Given multiple year benefit one may determine the threshold of initial investment for the bank. This initial benefit would be for changes in IT systems in order to effect the change from TSA to AMA.

5.2 Suggested recommendations for further research

The AMA developed and applied model uses a total of 27 classes (largely dependent on the structure of the subject matter bank), of which only 16 classes had more than 25 data points. The limited data points, which is bound to be a challenge across all banks in South Africa with ambitions to move from TSA to AMA, results in model being mainly scenario-driven. The direct role of ILD within the proposed AMA model is thus limited. This resultant number is considered to be relatively low (at 5/27). Plausible solutions to this predicament which requires further research could be found through allowing for evaluation of the "second best" ILD model, by modelling a unique body severity distribution at enterprise level, and applying it to different business units, or by using a coarser level of granularity which could increase the accuracy of the estimation using ILD and its overall influence on the resulting capital estimates.

Further research should also be considered to evaluate a more direct use of ELD. This could be achieved for example by mixing at either data level (i.e. "pooled data") or severity distribution (i.e. mixture of distributions) level, ILD and ELD components (Zhou, Giancometti, Fabozzi and Tucker, 2012). The methodologies in combining external and internal data are strongly related to the quality of the external databases. At the time of authoring this thesis, the available external databases did not meet all the quality criteria expected for a statistical use (threshold for fitting, categorisation, firm's figures for scalability). Therefore, these methodologies were not implemented in this thesis. One of the possible theories is the Credibility Theory. The insurance industry traditionally has developed and used credibility theory to deal with situations in which data is obtained from different sources. For a given population distribution that one estimates, the data from each source may be useful in describing the characteristics of the distribution, but no source can be used alone to give a full story. To paint a balanced picture, one may use a weighted average of the parameters estimated from several sources. The determination of the weights may depend on certain characteristics of the population distribution that is known a priori.

Alternative methods such as the extreme value theory, non-parametric empirical sampling, Markov Chain Monte Carlo (MCMC), and Bayesian approaches could be used in further studies.

The incorporation of a well-reasoned estimate of diversification benefits may be factored in at the group-wide level or at the banking subsidiary level subject to supervisory approval (BCBS, 2006). In order to take into account the diversification effect, the correlation between the different operational risk cells (ORC) has to be measured or estimated. When losses are aggregated across risk categories to calculate diversified total risk for a business unit, one technical issue that arises is how to account for correlations among the categories. In most South African banks, there is rarely enough data to support comprehensive correlation analysis. Moreover, it is strenuous to incorporate correlations into the mechanical process of calculating total loss exposure unless the joint distribution is the normal distribution (which is very unlikely to be the case). After all, correlations alone do not define the behaviour of losses across different categories in terms of a joint probability distribution. Finally, the currently available methods for calculating aggregate distributions in the actuarial framework models aggregate distributions through frequency and severity but does not address the correlation issues well. No currently available framework effectively addresses correlation while also directly modelling aggregate distributions, making this a worthwhile further research note.

5.3 Conclusion

The overall outcome of the research is fairly satisfactory as supported by the ultimate results, both the TSA and AMA quantification techniques applied were compliant with the SARB and the BCBS list of requirements. In this chapter, recommendations for further research and analysis on the model implementation and methodology have been identified. These recommendations are concerning possible areas of improvement in the model theory (post assessment of the model results), the quantification methodology overall and capital calculation process for assurance in the consistency of the capital calculation parts. The general recommendation on the area of further research concerns the use of the available internal data, whose influence could possibly be increased and ultimately improve accuracy. Also additional investigations with regard to the external data, scaled according to the risk profile of the bank, should be looked at so as to have more influence on the capital model. Additionally, continued research should be done for instances where no data collection is possible, to strongly assess market best practice. Overall the identification of a list of areas of further analysis (post assessing the results) is natural for any research article and does not indicate the presence of elements that are able to cause severe misspecification of the risk profile of a would be AMA applicant Bank. The author anticipates that this thesis though done in a case study format owing to data privacy restrictions (effectively limiting the number of data sets that could be used for this research), will have a far reaching practical impact for would be South African financial institutions that are currently on TSA. This thesis will aid them in coming up with an AMA framework, and ultimately assist in their attainment of a + / - 12% relief in operational risk regulatory capital, as granular detail on how to implement an LDA [that is fully compliant with all international standards] is extensively discussed.

Post completion of this piece of work, the Basel II committee has announced its intentions to possibly replace all existing and proposed methods with a Standardised Measurement Approach (SMA). On March 4, 2016, the Basel Committee released for consultation the new SMA, which is intended to replace all previous approaches including the AMA to calculating how much capital banks must set aside to cover operational risks. The key criticism against AMA by the Basel Committee has been its extensive complexity and it being inconsistently applied thus producing wildly divergent capital levels across the banks. The Committee has described the method as being difficult to implement and having various possibilities that can be adopted in its implementation leading to major differences across banks (Hegarty, M, 2015).

However, the authors' view is that AMA has been a leap frog in the evolution of understanding operational risk. If there is considerable need for comparison across banks, and model simplicity, Basel Committee would rather focus on possibly reducing the confidence level from 99.9% to 95%; restricting the range of distributions that might be used to fit ILD; increasing guidance with regard to Scenario building (taking into account Near Miss events that may serve as signalling devices for rare but big events) etc. The SMA is said to be "designed to suit all banks, irrespective of their size and risk profile". However, the author believes that operational risk by its very nature is idiosyncratic to the bank's processes, people, systems and such making it highly incomprehensible that a singular formula based on a Business Indicator (BI) and ILD Loss Factor (over a 10 year period), can be so structured to fully describe the unexpected loss patterns for each bank across the world.

For South African banks in particular, the South African Reserve Bank has insinuated[32] (an unofficial statement) that models are likely to be relegated to Pillar II reporting (Economic Capital (ECAP) calculations), as opposed to Pillar I (Regulatory Capital). The final decision on the fate of AMA shall be made at the close of 2016, South African banks should view this as an opportunity to so alter their models to have a more increased focus on risk management (as the regulatory stick is removed). Thus since banks will need to continue to quantify operational risks for ECAP purposes, the quantification may now use approaches that best meet business needs and achieve more objectives than just capital calculations. This research work will thus continue to serve its intended purposes albeit for ECAP purposes as opposed to RegCap.

[32] http://www.oliverwyman.com/content/dam/oliver-wyman/global/en/2016/mar/Oliver-Wyman-Beyond-AMA.PDF

REFERENCES

Afambo, A. (2005). 'Operational risk capital provisions for banks and insurance companies', Department of Risk Management and Insurance Georgia State University, Available from: <http://scholar.google.co.za/scholar_url?url=http%3A%2F%2Fwww.soa.org%2Flibrary%2Fresearch%2Factuarial-research-clearing-house%2F2006%2Fjanuary%2Farch06v40n1-xv.pdf&hl=en&sa=T&oi=ggp&ct=res&cd=0&ei=4mc3V7WBINCTmgHw64OoCQ&scisig=AAGBfm1lpbg4vR6XjwQLoAlF87mIpoXbOw&nossl=1&ws=1366x673>

Alderweireld, T., Garcia, J. and Léonard, L. 2006. 'A practical operational risk scenario analysis quantification', *Risk.Net*. 1 February. 93 – 95.

Allen, L. and Bali, T.G. (2004). '*Cyclicality* in Catastrophic and Operational Risk Measurements', Working Paper, City University of New York, September.

Anderson, T. W. and Darling, D. A. 1954. 'A test of goodness of fit', *Journal of the American Statistical Association,* 48(268): 765 – 769.

Baud, N., Frachot, A. and Roncalli, T. 2003. 'How to avoid over-estimating capital charge for operational risk?', Operational Risk – Risk's Newsletter. February.

BCBS. 2003. 'Basel II: The New Basel Capital Accord - third consultative paper' [online]. Switzerland: Bank for international settlements.
Available from: http://www.bis.org/bcbs/bcbscp3.htm
[Accessed: 15 May 2016]

BCBS. 2006. 'International convergence of capital measurement and capital standards - a revised framework, comprehensive version' [online]. Switzerland: Bank for international settlements.
Available from: < http://www.bis.org/publ/bcbs128.pdf >
[Accessed: 10 April 2015]

BCBS. 2009. 'Basel II: Strengthening the resilience of the banking sector [online]. Switzerland: Bank for international settlements.
Available from: <http://www.bis.org/publ/bcbs164.pdf>
[Accessed: 15 May 2016]

BCBS. 2011. 'Operational risk – supervisory guidelines for the advanced measurement approaches' [online]. Switzerland: Bank for international settlements.
Available from: < http://www.bis.org/publ/bcbs196.pdf >
[Accessed: 10 April 2015]

Berger, J. 1985. 'Statistical Decision Theory and Bayesion Analysis'. New York: Springer-Verlag.

Bocker, K. and Kluppelberg, C. 2005. 'Operational VaR: a closed form solution', RISK Magazine. December. 90–93.

Bühlmann, H. and Gisler, A. 2005. 'A course in credibility and its applications'. Berlin Heidelberg: Springer.

Chernobai, A., Rachev, S. T. and Fabozzi, F. J. 2012. 'Composite goodness-of-fit tests for left-truncated loss samples', In: Lee, C-F. ed. Handbook of financial econometrics and statistics. New York: Springer. 575-596.

Chernobai, A. and Rachev, S. T. 2006. 'Applying robust methods to operational risk modelling', *Journal of Operational Risk*, 1(1):27-41.

Cruz, M. G. 2002. 'Modeling, Measuring and Hedging Operational Risk'. Chichester: Wiley.

De Fontnouvelle, P., DeJesus-Rueff, V., Jordan, J. and Rosengren, E. 2003. 'Using loss data to quantify operational risk' [online]. United States: Stern New York University.
Available from: < http://www.stern.nyu.edu/om/faculty/pinedo/ofs/operationalloss.pdf >
[Accessed: 15 April 2015]

De Fontnouvelle, P., Rosengren, E. and Jordan, J. 2004. 'Implications of Alternative Operational Risk Modelling Techniques [online]. United States: University of Chicago press.

Available from: < http://www.nber.org/chapters/c9617.pdf >
[Accessed: 15 April 2015]

De Jongh, De Jongh, De Jongh and van Vuuren (2012) entitled 'A review of operational risk in banks and its role in the financial crisis' (*South African Journal of Economic and Management Studies*, 16(4), 364-382)

Diebold, F. X., Schuermann, T. and Stroughair, J. D. 1998. 'Pitfalls and opportunities in the use of extreme value theory in risk management'. In. Refenes, A. P. N., Moody, J. D. and Burgess, A. N. eds., Advances in computational finance. Amsterdam: Kluwer Academic Publishers. 3–12.

Dutta, K. and Perry, J. 2006. 'A tale of tails: An empirical analysis of loss distribution models for estimating operational risk capital' [online]. United States: The Federal Reserve Bank of Boston.
Available from: < https://www.bostonfed.org/economic/wp/wp2006/wp0613.pdf >
[Accessed: 15 April 2015]

Efron. B. F. 1979 'Bootstrap Methods: Another Look at the Jackknife'. *Annals of Statistics Volume 7, Number 1, 1-26*

Efron, B. F. and Tibshirani, R. J. 1993. An Introduction To The Bootstrap. London: Chapman and Hall.

El Arif, F. Z. and Hinti, S. 2014. 'Methods of Quantifying Operational Risk in Banks: Theoretical approaches'. *American Journal of Engineering Research*, Vol 3, Issue 03, 283 – 244.

Embrechts, P., Kaufmann, R., and Samorodnitsky, G. (2004). 'Ruin theory revisited: Stochastic models for operational risk', http://www.Math.Ethz.Ch/~baltes/ftp/ersamo.Pdf. Risk Management for Central Bank Foreign Reserves: 243-261.

Embrechts, P., Kluppelberg, C. and Mikosch, C. 1997. 'Modelling extremal events for insurance and finance'. New York:Springer.

Embrechts, P., Lindskog, F. and McNeil, A. J. 2003. 'Modelling dependence with copulas and applications to risk management'. In: Rachev, S. T. ed. Handbook of heavy tailed distributions in finance. Amsterdam: Elsevier/North-Holland. 307-327.

Ergashev, B. 2008. 'Should risk managers rely on maximum likelihood estimation method while quantifying operational risk?', *Journal of Operational Risk*, 3(2):63-86.

Fitch Risk Management. (2004). 'Fitch sees hitch in Basel operational risk rules'. Technical report, Reuters 04 21 04 5 2/ AM ET.

Frachot, A., Moudoulaud, O. and Roncalli, T. 2003. 'Loss distribution approach in practice' [online]. France: Thierry-Roncalli.
Available from: < http://www.thierry-roncalli.com/download/lda-practice.pdf >
[Accessed: 10 April 2015]

Francesco, S. and Todri Ardita, M (2012). 'Why the Implementation of Advanced Measurement Approach in Operational Risk Management Isn't A So Good Idea: The Albanian Banking System Case'. *International Journal of Business and Commerce* Vol. 1, Issue No.12, [47-55].

Froot, K. A. 2003. 'Bank Capital and Risk Management: Operational Risks in Context.'[PowerPoint Presentation] "No date". Federal Reserve Bank of Boston, Boston.

Hegarty, M. (2015). 'Basel committee to consult on scrapping op risk modelling' by [online]. Available at:http://www.risk.net/operational-risk-and-regulation/news/2429034/basel-committee-to-consult-on-scrapping-op-risk-modelling].
[Accessed on 02/05/2016].

Kaiser, T. and Kohne, M. (2006). An Introduction to Operational Risk. London: Risk Books, (Chp 3).

King, J. L. 2001. 'Operational risk: Measurements and Modelling'. Chichester: Wiley.

Klugman, S. A., Panjer, H. H. and Willmot, G. E. 1998. 'Loss models: from data to decisions. New Jersey: Wiley.

Knuth, D. E. 1998. The art of computer programming, vol.2: seminumerical algorithms. 3rd ed. Reading: Addison-Wesley.

Lambrigger, D. D., Shevchenko, P. V. and Wüthrich, M. V. 2007. 'The quantification of operational risk using internal data, relevant external data and expert opinions', *Journal of Operational Risk*, 2(3):3-27.

Lavaud, S. and Lehérissé, V. 2014. 'Goodness-of-fit tests and selection methods for operational risk', *Journal of Operational Risk*, 9(3):21-50.

Laycock.M. 2014. Operational risk quantification: the advanced measurement approach. *Thomas Reuters.* accelus.thomsonreuters.com

Mignola, J. and Ugoccioni, R. 2006. 'Sources of uncertainty in modelling operational risk losses', *Journal of Operational Risk,* 1(2):33-50.

Morone, M., Cornaglia, A. and Mignola, G. 2007. 'Economic capital assessment via copulas: aggregation and allocation of different risk types' [online]. United States: Default Risk.
Available from: < http://defaultrisk.com >
[Accessed: 18 April 2015]

Moscadelli, M. 2004. 'The modelling of operational risk: experience with the analysis of the data collected by the Basel Committee' [online]. Italy: Banca d'italia.
Available from:
<http://www.bancaditalia.it/pubblicazioni /econo/temidi/td04/td517_04/td517/tema_517.pdf>
[Accessed: 20 April 2015]

Nash, R.A. (2003). 'The Three Pillars of Operational Risk, in Alexander, C. (ed) Operational Risk: Regulation, Analysis and Management. London: Prentice Hall-Financial Times', (Chapter 1).

Opdyke, J. D. 2014. 'Estimating operational risk capital with greater accuracy, precision and robustness', *Journal of Operational Risk*, 9(4):3-82.

ORX. 2010. ORX capital methodology survey 2010 [online]. Switzerland: ORX.
Available from: < https://www.orx.org/awg >
[Accessed: 20 April 2015]

Panjer, H. H. 2006. 'Operational risks: Modeling Analytics'. New York: Wiley

Peters, J-P. and Hübner, G. 2009. 'Modeling operational risk based on multiple expert's opinions'. In: Gregoriou, G. N. ed. Operational risk toward Basel III, best practices and issues in modeling, management and regulation. New York: Wiley. 3–21.

Reiss, R. D. and Thomas, M. 2001. 'Statistical Analysis of Extreme Values'. 2nd ed. Basel: Birkhauser.

Rebonato, R. (2007). 'The Plight of the Fortune Tellers: Why We Need to Manage Financial Risk Differently'. New Jersey: Princeton University Press, (Chapter 8).

Robert, C. P. 2001. The Bayesian choice: A Decision Theoretic Motivation. 2nd ed. New York: Springer-Verlag.

Shevchenko, P. V. 2010. 'Calculation of aggregate loss distributions', *The Journal of Operational Risk,* 5(2):3–40.

Shevchenko, P.V. 2010. 'Implementing loss distribution approach for operational risk', Applied Stochastic Models in Business and Industry, 26(3):277–307.

Shevchenko, P. V. 2011. Modelling Operational Risk Using Bayesian Inference. Berlin: Springer.

Shevchenko, P. V. and Wüthrich, M. V. 2006. 'The structural modelling of operational risk via Bayesian inference: combining loss data with expert opinions', *The Journal of Operational Risk*, 1(3):3 – 26.

Snyman, P. 2011. 'Risk–based capital measures for operational risk management' [online]. South Africa: North West University.
Available from: < http://hdl.handle.net/10394/7573 >
[Accessed: 18 April 2015]

Steinhoff, C. and Baule, R. 2006. 'How to validate op risk distributions' [online]. Denmark: Deriva.
Available from: < http://www.deriva.de/files/validateoprisk.pdf >
[Accessed: 25 April 2015]

Sundmacher, M. 2007. ‘The basic indicator approach and the standardised approach to operational risk: an example- and case study-based analysis [online]. United States: Social Science Electronic Publishing’.
Available from: < http://ssrn.com/abstract=988282 >
[Accessed: 10 April 2015]

Sundmacher. M. 2004 ‘Operational risk measurement in banks: arbitrage, adjustments and alternatives’. Electronic copy of this paper is available at: http://ssrn.com/abstract=963231. School of Economics and Finance. University of Western Sydney

Tsai, C-L. and Hurvich, C. M. 1988. ‘Regression and time series model selection in small samples’, *Biometrika,*76 (2):297 – 307.

Valova. I. 2011 ‘Basel II Approaches for the calculation of the regulatory capital for operational risk’. No 1 / 2011. Masaryk University, Faculty of Economics and Administration. Lipova 41a, 120 00 Brno.

Zhou, X., Giancometti, R., Fabozzi, F. J. and Tucker, A. H. 2012. ‘Bayesian estimation of truncated data with applications to operational risk measurement’, Quantitative Finance, 14(5):863-888.